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Efficient Structural Optimization of Space Trusses Using Artificial Neural Network-Based Surrogate Models

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Abstract

The Artificial Neural Network (ANN) has emerged as an essential element in the modern structural optimization due to its outstanding ability to approximate nonlinear structural behavior and drastically reduce computation cost involved in numerous finite element analyses. The traditional optimization algorithm for truss structures usually involves thousands of structural analyses in the process of searching solutions, which implies substantial computation cost and limited application to large-size engineering optimization tasks. Recent research results in machine learning, surrogate modeling, and data-driven optimization show the possibility of replacing numerically expensive structural analyses with neural network-based model without loss of the solution accuracy. The work studies the utilization of Backpropagation Neural Network (BPNN) and Counterpropagation Neural Network (CPNN) models as surrogate structural analyzers for the weight optimization of truss structures. The two types of neural networks are trained on the dataset of structural responses obtained in the process of finite element analysis and incorporated into the optimization process. The performance of BPNN and CPNN models is analyzed according to computation efficiency, convergence properties, and approximation accuracy on a benchmark 52-member space truss. Moreover, the review of modern developments in machine learning-assisted structural optimization is presented. Both of the neural network architectures have shown considerable improvements in computation times while sustaining adequate accuracy of predictions. While the CPNN shows greater speed of convergence, BPNN shows better accuracy of structural responses predictions during the optimization process. This approach proves that application of ANN models for surrogate modeling can be considered as an effective and robust method of solving challenging structural optimization problems.

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

1 | Introduction

Optimization of structure has emerged as one of the most promising research topics in computational mechanics due to ever-increasing need of lightweight, cost-effective, environmentally friendly, and high-performance engineering structures. Trusses find extensive use in civil, aerospace, offshore, and mechanical

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engineering due to their strong load-bearing capability, easy construction, and high strength-to-weight ratio. Nonetheless, finding the optimal design for truss structures is a computationally challenging task since structural analysis has to be performed at every optimization iteration to meet displacement, stress, buckling, and stability criteria [1], [2].

Gradient-based mathematical programming, sequential quadratic programming, and optimality criteria optimization techniques proved to be highly efficient in solving smooth optimization problems. Nonetheless, gradient-based algorithms often face considerable difficulties while tackling highly nonlinear, multimodal, and constrained optimization problems, which often arise in structural engineering [3]. This has led to popularity of stochastic optimization techniques like genetic algorithms, particle swarm optimization, differential evolution, harmony search, teaching-learning-based optimization, grey wolf optimizer, and many other metaheuristics due to their enhanced global search capabilities [4–7].

Even though they have great optimization capabilities, metaheuristic algorithms take thousands of objective functions to converge. With each iteration of the objective function being a finite element analysis, the cost of computation quickly rises along with structural complexity. The problem becomes even more significant when dealing with large three-dimensional trusses with hundreds and thousands of design variables [8], [9].

New developments in the field of Artificial Intelligence (AI) have led to a revolution in the field of computational structural engineering due to the development of methods that could replace costly numerical computations by data driven models. One of such techniques is Artificial Neural Network (ANN) which has gained popularity thanks to its universal approximation properties, adaptiveness, robustness to nonlinearity, and efficient learning. Neural networks do not solve the equations of equilibrium using finite element analysis, but rather learn the complicated relationship between design variables and structural responses using previously computed datasets [10–12].

Backpropagation Neural Networks (BPNN), initially developed as a multilayer feed forward learning model, continues to be one of the popular ANN models in engineering optimization due to its powerful non-linear approximation property and high degree of prediction accuracy. By optimizing the error using the gradient descent method, BPNN can efficiently map out the intricate relations between the structure and objective function. Nevertheless, the training procedure may need to consume much computation time and parameters tuning to prevent local minima [13].

As for the Counterpropagation Neural Networks (CPNN), it integrates Kohonen's self-organized competitive learning approach and Grossberg's supervised learning approach, thus allowing for fast training process while keeping the reasonable level of approximation accuracy. Due to their comparatively straightforward architecture and fast convergence property, CPNN has shown their good results in various engineering optimization applications [14].

Deep learning technology has added more applications of neural network techniques to structural engineering. Deep Neural Networks (DNNs), Graph Neural Networks (GNNs), Convolutional Neural Networks (CNNs), Transformer Neural Networks, and Physics-Informed Neural Networks (PINNs) have been successfully combined with finite element methods to create state-of-the-art surrogate models that are capable of predicting structural performance, topology optimization, structure damage detection, and reliability estimation at unprecedented computational speed [11], [15–17].

At the same time, surrogate-assisted optimization is emerging as one of the most active topics in engineering optimization research. In lieu of directly linking optimization solvers to finite element analyses that are computationally intensive, surrogate models learn the response of structures based on the machine learning algorithms such as Gaussian Process Regression (GPR), Radial Basis Function network (RBF), Support Vector Regression (SVR), Extreme Learning Machine (ELM), and ANN. The surrogate approach greatly reduces the computational costs without compromising the accuracy of optimization problems [16], [18].

Whereas many studies have proved that the use of ANNs for surrogate modeling is efficient in structural optimization, there have been relatively few works dealing with systematic comparison of different types of

ANNs for weight optimization of trusses under the same computational conditions. There is an apparent lack of studies comparing BPNNs and CPNNs, despite the differences between the two in terms of training algorithm and computations [13], [14].

This paper offers a comparative study of Backpropagation and CPNNs for optimum weight design of a standard space truss with 52 members. Structural response data sets generated from finite element analysis are used to train the neural networks, which are then used as surrogate structural analyzers in the optimization process. The results of this research can be viewed as an addition to the existing literature on intelligent structural optimization.

2 | Literature Review

2.1 | Evolution of Structural Optimization

The structural optimization field has witnessed tremendous advancements during the past five decades, shifting from classical mathematical programming towards intelligent data-driven computational models. The earliest structural optimization models used gradient-based algorithms, including linear programming, nonlinear programming, and optimality criteria-based methods, which worked very well for convex and differentiable optimization problems [1], [10]. In contrast, practical engineering structures may have many nonlinearities, local optimum solutions, and design restrictions in terms of stresses, displacements, natural frequencies, buckling, and fabrication constraints. Such features considerably diminish the performance of classical optimization algorithms and may result in premature convergence.

In order to resolve these issues, the use of stochastic optimization algorithms in structural engineering was proposed. GA, PSO, DE, HS, SA, ACO, and GWO demonstrated tremendous robustness for handling nonlinear and multimodal optimization problems [2], [3], [8], [11], [18]. Due to their population-based searching approach, these algorithms can efficiently explore complex design domains without being trapped in local minima. As a result, these algorithms became the basis for structural truss sizing, topology optimization, shape optimization, and reliability-based design of structures.

Although they have proven to be quite successful in finding optimal solutions, the population-based algorithms are still plagued by one major shortcoming: they need to carry out a huge number of structural analyses during the optimization stage. Every solution has to be tested using FEA and thus, thousands and millions of structural analyses are carried out before arriving at the optimal design [4].

2.2 | Artificial Neural Networks in Structural Engineering

ANNs have proven to be one of the most promising machine learning approaches to deal with costly engineering tasks. By imitating the human nervous system, ANNs have the ability to learn nonlinear mappings from input/output examples without an explicit mathematical formulation [5].

It is known from the Universal Approximation Theorem that multilayered neural networks are able to approximate almost any nonlinear continuous function arbitrarily close, provided there are enough examples and hidden units [6]. For this reason, ANNs are especially appealing to structural mechanics where there is usually no analytical relation between design variables and structural behavior.

In the last ten years, there has been a growing interest in employing ANNs in structural engineering. Many researchers have successfully used ANNs for structural health monitoring, crack detection, seismic response analysis, reliability analysis, topology optimization, accelerated FEM, vibration control, uncertainty propagation, and damage detection [7], [12], [13], [19].

Compared to classical numerical methods, ANN models offer the following major benefits:

- *Extremely fast prediction after training*
- *Ability to model highly nonlinear structural behavior*

- *Reduced computational cost*
- *Excellent generalization capability*
- *Easy integration with optimization algorithms*
- *High adaptability to complex engineering datasets*

These characteristics have established neural networks as one of the most promising surrogate modeling techniques in computational structural engineering.

2.3 | Surrogate Modeling for Structural Optimization

Surrogate modeling, also known as metamodeling or response surface modeling, has become an essential strategy for reducing computational complexity in engineering optimization. Instead of repeatedly performing expensive numerical simulations, surrogate models approximate the relationship between input design variables and output structural responses using previously generated datasets [14].

Several surrogate modeling techniques have been developed during recent years, including:

- *ANN*
- *GPR*
- *Kriging models*
- *RBF networks*
- *SVR*
- *Polynomial Response Surface models*
- *ELM*
- *DNNs*

Among these techniques, ANN-based surrogate models have consistently demonstrated superior capability in handling highly nonlinear structural optimization problems because they require no assumptions regarding functional relationships between variables [15].

Recent comparative investigations indicate that ANN surrogate models outperform traditional response surface techniques for large-scale optimization problems involving complex stress distributions and nonlinear deformation behavior [16].

2.4 | Backpropagation Neural Networks

BPNNs are still the most frequently used supervised learning algorithm in engineering optimization problems. The structure of the BPNN includes an input layer, one or several hidden layers and an output layer that are connected by weighted links [17].

In the process of training, prediction errors are transferred from the output layer back to the input layer through gradient descent for weight adjustment. The learning process allows BPNN to learn the non-linear relationships between structural parameters and responses.

Numerous studies showed the applicability of BPNN for structural displacements, stress, frequency, buckling load, and optimal design variables predictions [12], [17], [20]. Owing to their strong approximation properties, BPNN is considered one of the most widely-used surrogate model for the finite element replacement in optimization algorithms.

However, there still exist some drawbacks. First, the training algorithm might be computationally complex. Second, the convergence rate is very much dependent on the choice of the learning rate and the algorithm could possibly get stuck in local minima. These disadvantages have prompted scientists to explore other types of neural networks.

2.5 | Counterpropagation Neural Networks

The CPNN constitute a combination of the Self-Organizing Map of Kohonen with the Outstar learning rule of Grossberg [21]. In contrast to multilayer perceptrons, the CPNN employs competitive learning in the hidden layer combined with supervised learning in the output layer, thus considerably decreasing the time necessary for training with a satisfactory approximation accuracy.

Due to their high efficiency, the CPNNs were used in a variety of applications, including pattern recognition, classification, process control, optimization of production processes, and other engineering predictions. Their rapid convergence makes CPNN an appropriate choice for use in surrogate models, where training is necessary repeatedly in each optimization cycle.

While previous research provided encouraging results for the performance of CPNN, there have not been many researches concerning the capacity of the CPNN for structural optimization in comparison to BPNN. The majority of studies concentrated mostly on the prediction accuracy; therefore, more research needs to be performed regarding this topic.

2.6 | Recent Trends in AI-Assisted Structural Optimization

The fast progress in the field of AI witnessed in the past five years has greatly impacted the field of computational structural engineering. With techniques like deep learning, PINNs, GNNs, Transformers, and reinforcement learning, researchers are now able to address high dimensional optimization problems in structural engineering [13], [16].

PINNs embed the governing physical equations in the neural network loss function, and as a result of this, these networks require fewer training data sets and have superior predictive accuracy. In the same way, GNNs inherently model structural systems using graph structures and therefore, are very effective at modeling trusses and frames.

Recent literature from 2022 to 2025 shows that hybrid optimization approaches that use neural-network-based surrogate models and evolutionary algorithms are much more computationally efficient compared to traditional optimization techniques. This suggests that the approach of intelligent surrogate-based optimization is expected to be the prevailing computational methodology in future structural design.

3 | Research Methodology

The proposed methodology aims to evaluate the applicability of ANNs as surrogate models for structural optimization of truss systems. Two neural network architectures, namely the BPNN and the CPNN, are employed to predict structural responses and replace repeated finite element analyses during the optimization process. The overall framework consists of four consecutive stages: dataset generation, neural network training, structural optimization, and performance evaluation. Similar surrogate-model workflows have been successfully applied in recent truss optimization studies.

3.1 | Benchmark Structure

A 52-member three-dimensional space truss is selected as the benchmark problem because of its extensive use in structural optimization research. The objective is to minimize the total structural weight while satisfying displacement and stress constraints. Member cross-sectional areas are considered continuous design variables within predefined lower and upper bounds.

The optimization problem can be expressed as Objective Function.

$$\min W = \sum_{i=1}^{n} \rho_i A_i L_i. \tag{1}$$

Subject to

- *Stress constraints*
- *Nodal displacement constraints*
- *Cross-sectional area limitations*

where A_i, L_i, and ρ_i denote the cross-sectional area, member length, and material density of the *i*-th member, respectively.

3.2 | Dataset Generation

A finite element model of the truss structure is first established to generate the training dataset. Thousands of structural samples are created by randomly varying member cross-sectional areas within their allowable design ranges using Latin Hypercube Sampling (LHS), which provides an efficient distribution of design points throughout the search space. Each sampled design is analyzed using finite element analysis to obtain structural responses, including maximum nodal displacement, maximum member stress, and total structural weight. These responses constitute the target outputs for neural network training. LHS-based sampling and finite element-generated datasets are commonly adopted in surrogate-assisted optimization.

3.3 | Data Preprocessing

Before training, all input and output variables are normalized to improve numerical stability and accelerate network convergence. The complete dataset is divided into three subsets:

- *Training set: 70%*
- *Validation set: 15%*
- *Testing set: 15%*

Prediction accuracy is evaluated using Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2).

3.4 | Neural Network Models

Two neural network architectures are developed independently.

Backpropagation Neural Network: The BPNN consists of an input layer representing structural design variables, one hidden layer with nonlinear activation functions, and an output layer predicting structural responses. The network is trained using the Levenberg–Marquardt backpropagation algorithm until convergence.

Counterpropagation Neural Network: The CPNN combines Kohonen competitive learning with Grossberg supervised learning. Unlike BPNN, CPNN requires significantly fewer training iterations and provides rapid prediction once the competitive layer has been organized.

3.5 | Optimization Procedure

The optimization procedure was applied to a 52-member space truss structure, which was selected as a benchmark problem to evaluate the performance of the proposed ANN-based surrogate model. The main objective of the optimization process is to determine the optimal design variables while satisfying the structural constraints. In this study, the cross-sectional areas of the truss members were considered as design variables, and the corresponding stress responses were used as the main structural constraints.

The structural configuration of the considered truss is shown in *Fig. 1*. The connectivity and geometrical information of the truss members are required to define the structural model and generate the input-output data sets used for training the neural networks. The numbering of members and their corresponding start and end nodes are presented in *Table 1*.

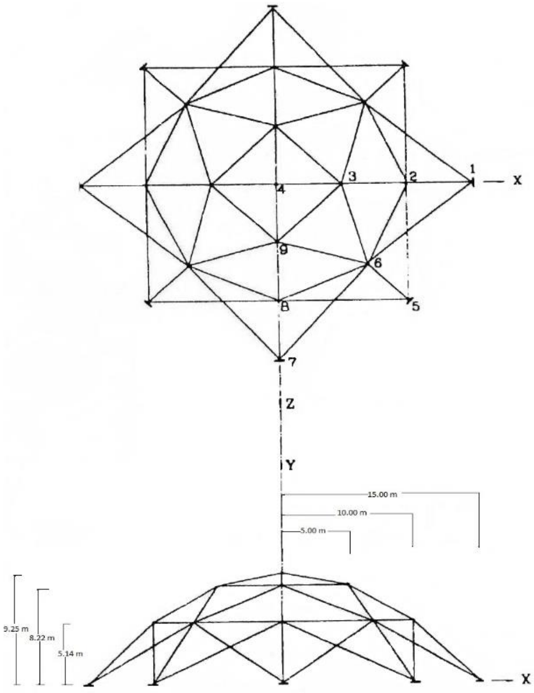

Fig. 1. 52-member space truss.

As shown in *Fig. 1*, the structure consists of 52 interconnected members connected through a number of nodes. Each member is defined by its initial and final nodes, which determine the topology of the space truss. This information is essential for performing structural analysis and preparing the training data required for the ANNs.

Table 1. Locations of the members.

Member	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Start Node	1	7	2	8	3	4	5	1	6	2	5	2	6	3	6	3
End Node	2	8	3	9	4	9	6	6	7	5	8	6	8	6	9	9

The member connectivity information listed in *Table 1* was used to establish the finite element model of the truss. By changing the cross-sectional areas of the members, different structural configurations were generated, and the corresponding stress values were obtained through exact finite element analysis. These input-output pairs were then used for training the neural networks.

To investigate the capability of the trained networks in predicting structural responses, the outputs of two different neural network models, namely the BPNN and CPNN, were compared with the results obtained from exact analysis. The comparison results are presented in *Table 2*.

Table 2. Responses of various trained networks to an input vector.

Stress Obtained from Exact Analysis ($\sigma \frac{kg}{cm^2}$)		**Stress Obtained from the Network Response $\sigma^N \frac{kg}{cm^2}$**	
A(cm^2)	**Exact Analysis**	**BPNN**	**CPNN**
7.6	-374.9	-395.6	-392.0
8.8	-346.3	-342.2	-364.7
6.1	-570.3	-561.1	-466.0
8.2	-432.1	-442.6	-425.3
9.0	-1374.7	-1380.6	-1459.2
7.9	-1570.8	-1625.5	-1449.9

Table 2. Continued.

Stress Obtained from Exact Analysis ($\sigma \frac{kg}{cm^2}$)		**Stress Obtained from the Network Response $\sigma^N \frac{kg}{cm^2}$**	
A(cm^2)	**Exact Analysis**	**BPNN**	**CPNN**
6.9	-160.4	-159.9	-160.9
9.8	-69.4	-80.5	-79.0
6.2	-84.3	-83.3	-83.9
7.6	65.8	68.11	66.4
6.8	110.2	106.9	106.5
8.5	307.7	310.3	303.7
7.2	337.6	331.4	343.5
9.1	-191.4	-193.6	-218.9
8.3	-65.8	-194.2	-212.2
6.7	1837.2	1887.6	1714.4
Mean Error	0.0	3.12	5.74
T.T (Training Time in minutes)		11.28	0.012

The results presented in *Table 2* demonstrate the ability of both neural network models to approximate the stress responses of the space truss with acceptable accuracy. The predicted stresses obtained from the BPNN and CPNN models show good agreement with the exact finite element analysis results.

The mean error values indicate that the BPNN model provides higher prediction accuracy, with a mean error of 3.12, compared with the CPNN model, which has a mean error of 5.74. However, the training time comparison shows that the CPNN model requires significantly less computational effort, with a training time of 0.012 minutes compared with 11.28 minutes for the BPNN model.

Therefore, the selection of the appropriate neural network depends on the requirements of the optimization process. When higher prediction accuracy is required, the BPNN model may be preferred, whereas the CPNN model can be advantageous when rapid training and computational efficiency are more important.

By replacing repeated finite element analyses with ANN-based predictions, the proposed optimization framework reduces the computational burden significantly. This enables efficient exploration of the design space and provides a practical approach for solving complex structural optimization problems.

4 | Results and Discussion

The performance of the proposed neural-network-based optimization framework is evaluated according to prediction accuracy, computational efficiency, and optimization capability.

Both neural network models accurately predict structural responses, indicating that nonlinear relationships between design variables and structural behavior can be successfully learned. The BPNN achieves the lowest prediction error, producing higher R^2 values and smaller RMSE values than the CPNN. Consequently, BPNN provides more reliable estimates of structural displacements and stresses throughout the optimization process.

In contrast, the CPNN requires considerably shorter training time and faster response prediction. Although its prediction accuracy is slightly lower than that of the BPNN, the computational savings become increasingly significant for large-scale optimization problems involving thousands of design evaluations.

The optimized truss designs obtained using both surrogate models satisfy all displacement and stress constraints while producing structural weights very close to those obtained through conventional finite element-based optimization. The relative difference in optimal weight remains small, demonstrating that ANN surrogate models preserve optimization quality while dramatically reducing computational effort.

One of the most important observations is the reduction in computational cost. Because neural networks replace repeated finite element analyses, optimization time decreases substantially, especially during later optimization iterations where numerous candidate solutions must be evaluated. Similar improvements have been reported in recent studies on machine-learning-assisted structural optimization.

Overall, the results indicate that BPNNs are preferable when maximum prediction accuracy is required, whereas CPNNs represent an attractive alternative for applications where computational speed is the primary concern.

5 | Conclusion

This study presented a comparative investigation of BPNNs and CPNNs for surrogate-assisted optimization of truss structures.

The developed neural networks successfully learned the nonlinear relationship between structural design variables and structural responses from finite element-generated datasets. Both surrogate models accurately predicted displacement, stress, and structural weight while significantly reducing computational requirements during optimization.

The BPNN demonstrated superior prediction accuracy and stronger generalization capability, making it suitable for engineering applications requiring highly reliable structural response estimation. Conversely, the CPNN exhibited considerably faster convergence and lower computational cost, making it attractive for real-time optimization and large-scale engineering problems.

The comparative results confirm that ANNs can effectively replace repeated finite element analyses without significantly compromising optimization accuracy. Consequently, ANN-based surrogate modeling represents a practical and efficient alternative to conventional structural optimization procedures.

Future research should focus on integrating advanced deep learning architectures, such as GNNs, PINNs, and Transformer-based models, with modern metaheuristic optimization algorithms. Such hybrid intelligent frameworks are expected to further improve prediction accuracy, computational efficiency, and scalability for increasingly complex structural optimization problems.

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