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Geometrically Nonlinear Shape Optimization of Elasto-Plastic Trusses Using a Neural Network-Assisted Genetic Algorithm

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Abstract

This paper presents a novel optimization framework for trusses that incorporates elasto-plastic material behavior and accounts for geometric nonlinearity to determine the optimal structural shape, thereby minimizing plastic deformations and material usage to ensure a safe and cost-effective design. To achieve this objective and to guarantee reliable structural behavior, Geometrical and Material Nonlinear Analysis (GMNA) was performed using the Finite Element Method (FEM), and the complementary strain energy was calculated to evaluate the structure's plastic performance. Due to the high computational demand of GMNA, a Neural Network-Assisted Genetic Algorithm (NNAGA) was applied, which learns intelligently from the data generated during the iterative design process and significantly accelerates the convergence of the optimization. The proposed methodology was validated through a benchmark numerical example involving a 33-bar truss. The obtained results demonstrated the efficiency of the developed framework in minimizing plastic deformations while simultaneously reducing material usage, outperforming a conventional genetic algorithm (GA) in terms of effectiveness.

Keywords: structural optimization, neural network, genetic algorithm, elasto-plastic design, large deformations, trusses.

1 Introduction

Steel trusses are widely used in construction for applications such as towers [1], bridges [2], and roofs [3]. Due to the complexity of these structures, the design process must be carried out with care to ensure safe and reliable performance. Incorporating nonlinear effects—such as inelastic material behavior and large deformations—can contribute to a more accurate and thoughtful design [4–6]. In this context, plastic analysis offers valuable insights into complex structural responses, including post-yield behavior, thereby enhancing overall safety. Applying such a methodology supports the development of robust designs and helps prevent catastrophic failures such as [7,8].

Plastic analysis of structures generally involves the characterization of inelastic deformations, which remain permanent even after unloading. To achieve this, various theoretical approaches have been proposed in the literature [9–14]. A subset of these methods is based on limiting plastic strains and residual displacements [15–17], which has contributed to the development of advanced computational design techniques that successfully address the optimization of discrete trusses [18–20]. Through numerical examples, these approaches have demonstrated the effectiveness of plastic analysis. However, accurately accounting for inelastic deformations often results in significantly increased computational demand due to the strongly nonlinear material behavior.

In addition to plastic constitutive relation, other nonlinear effects such as large deformations [21–23] contribute to increased complexity in both optimization and computational effort. Consequently, to address these challenges more effectively, recent research has focused on combining various machine learning techniques with metaheuristic algorithms [24–27]. These studies typically aim to determine the optimal cross-sectional areas of individual bar members, framing the task as a size optimization problem. This approach aligns with the classical categorization of structural optimization, which also includes shape and topology optimization [28].

In this paper, a Neural Network-Assisted Genetic Algorithm (NNAGA) based optimization framework is proposed to determine the optimal shape of a truss by adjusting the predefined joint coordinates, with the aim of enhancing plastic performance while simultaneously reducing structural weight. This was achieved by incorporating Geometrical and Material Nonlinear Analysis (GMNA) using the Finite Element Method (FEM). The proposed approach was tested on a simply supported 33-bar truss structure, and the results were compared to those obtained using a conventional Genetic Algorithm (GA) based optimization, thereby verifying its efficiency. The outcomes demonstrated the potential and effectiveness of the developed framework in achieving a safer and more cost-effective design by eliminating plastic deformations, reducing structural weight, and enhancing convergence through the integration of a Neural Network (NN).

2 Elasto-plastic optimizations of trusses

This section provides an overview of the elasto-plastic optimization approach applied to truss structures, with the aim of determining the optimal shape of the selected numerical example. In structural design, the primary objective is to maximize performance while minimizing material usage, thereby achieving a safe and economically efficient configuration. Consequently, in the case of elasto-plastic truss optimization, plastic response must also be evaluated and controlled alongside weight reduction.

To characterize the plastic behavior of the structure, the complementary strain energy of residual forces is utilized in this research. Previous studies have demonstrated that this concept can be effectively applied for this purpose through the development of advanced computational methods [29–33]. The complementary strain energy W_p associated with residual forces is given by the following equation:

$$W_p = \frac{1}{2E}\sum_{i=1}^{n}\frac{l_i}{A_i}N_i^{R^2} \leq W_{p0} \text{ where } i = 1, 2, 3, \dots\dots, n \tag{1}$$

where W_{p0} is the limiting value of allowable complementary strain energy, E denotes the elastic modulus of the material, l_i is the length of the i-th bar, and A_i represents its corresponding cross-sectional area. Furthermore, N_i^R is the residual force in the respective element, which, in the case of an applied load P_0, can be expressed as the difference between the internal plastic force N^{pl} and the internal elastic force N^{el}, as follows:

$$N^R = N^{pl} - N^{el} \tag{2}$$

where

$$N^{el} = F^{-1}G^T K^{-1} P_0 \tag{3}$$

Here, G corresponds to the geometry matrix, K to the stiffness matrix, and F to the flexibility matrix.

In the context of the complementary strain energy of residual forces, the shape optimization problem for elasto-plastic planar truss structures—characterized by nodal coordinates x_j and y_j and constructed with a uniform cross-sectional area A—can be formulated as follows:

$$\text{minimize:} fitnes = f(G_s) + p_1(W_p) + p_2(P) \tag{4a}$$

where

$$f(G_s) = \frac{\rho\sum_{i=1}^{n} A l_i}{G_{s,0}}; \tag{4b}$$

$$p_1(W_p) = \frac{\frac{1}{2E}\sum_{i=1}^{n}\frac{l_i}{A}N_i^{R^2}}{W_{p0}}; \tag{4c}$$

$$p_2(P) = 1 - \frac{P}{P_0}; \tag{4d}$$

Subject to:

$$x_{j,0} + x_{min} \leq x_j \leq x_{j,0} + x_{max}; \tag{4e}$$

$$y_{j,0} + y_{min} \leq y_j \leq y_{j,0} + y_{max}; \tag{4f}$$

$$N^{el} = F^{-1} G^T K^{-1} P_0; \tag{4g}$$

$$\overline{N^{pl}} \leq N^{pl} \leq \overline{N^{pl}}; \tag{4h}$$

As presented in Equation (4a), the fitness function consists of three main components. Equation (4b) represents the ratio of the structural weight G_s to the maximum allowable weight $G_{s,0}$, ensuring that an economically efficient configuration is achieved. Additionally, Equation (4c) serves as the first penalty function, associated with the calculated complementary strain energy. In the case of fully elastic behavior, $p(W_0)$ remains zero; thus, weight minimization becomes the sole objective during the optimization process. Finally, Equation (4d) introduces the second penalty function, where P_0 is the predefined load value, and P is the actual load reached during the loading history. This term enforces that the structural load-bearing capacity satisfies the design requirement, such that the achieved load P equals the specified load P_0, in contrast; otherwise, $p(P)$ becomes nonzero.

Furthermore, Equation (4e) and Equation (4f) defines the design domain used to adjust the specified joint coordinates x_j and y_j thereby determining the optimal shape of the structure. Here, $x_{j,0}$ and $y_{j,0}$ denote the initial coordinates of the j-th node. During the optimization process, these coordinates are allowed to vary within the range $[x_{min}, x_{max}]$ in the horizontal direction and $[y_{min}, y_{max}]$ in the vertical direction. Finally, Equation (4g) defines the calculation of the elastic internal forces, while Equation (4h) represents the plastic limit condition, where $\overline{N^{pl}}$ denotes the ultimate plastic load capacity.

The problem formulation presented through Equations (4a)–(4h) directs the optimization toward solutions that minimize plastic deformations, while ensuring that the structure withstands the required load capacity and achieves a reduction in weight. In conclusion, the two penalty functions enforce that the structural performance requirements are met, while the objective term $f(G_s)$ promotes an economically efficient design by adjusting the nodal coordinates x_j and y_j within their predefined ranges.

3 Neural Network-Assisted Genetic Algorithm (NNAGA) framework

In this section, the main components of the developed optimization framework are presented. The proposed method integrates a Neural Network (NN) into a Genetic Algorithm (GA) to improve convergence and increase the probability of finding the global optimum solution. The implementation was carried out using the PYTHON programming language and ABAQUS [34] software, and incorporates the formulations defined in Equations (4a)–(4h).

The GA is a widely used metaheuristic optimization technique, commonly applied to various practical engineering problems [35]. Inspired by the principles of natural evolution, this method operates by evaluating a population of potential candidate solutions, where the fitness value determines the quality and suitability of each solution. During the optimization process, the genetic operators—selection, crossover, and mutation—are responsible for guiding the search and maintaining convergence from generation to generation in an iterative manner. Over the years, GA has proven its efficiency in solving a wide range of problems within the field of civil engineering [36–39].

The other employed technique, the NN, is a computational model designed to capture nonlinear relationships between input and output data, mimicking the function of the human neural system. Its fundamental unit is the neuron, in which the activation function introduces nonlinearity into the model. In a fully connected NN, neurons are hierarchically organized in a layered structure, where each neuron in one layer is connected to every neuron in the next. The outputs of lower-layer neurons undergo successive transformations as they propagate through the network, ultimately reaching the upper layers to generate the final output. This algorithm has demonstrated its efficiency across numerous applications in the field of civil engineering [40].

The fundamental concept of the developed methodology is to enhance the performance of the GA by incorporating a fully connected NN to generate a new population based on data from previous generations. This introduces an additional step into the standard GA workflow, wherein a portion of the new population is produced using predictions from the NN. This process consists of three key subcomponents:

a) Data preparation: In this step, data generated during the GA operation is collected. The optimized nodal coordinates $[x_j, y_j]$ are used as inputs for the NN, while the corresponding penalty function values $p_1(W_p)$ and $p_2(P)$ serve as outputs. Subsequently, the input values are normalized based on their maximum ($x_{j,max}$, $y_{j,max}$) and minimum ($x_{j,min}$, $y_{j,min}$) values. This prepared data is then used to train NN.

b) Create and train NN: This step involves constructing the NN architecture based on predefined hyperparameters, including the number of hidden layers, the number of neurons per layer, the type of activation function, and the learning rate. Once the structure is defined, the training process begins using the backpropagation algorithm [41]. During training, the error between the predicted and actual output values is evaluated using the Mean Squared Error (MSE) loss function. The outcome of this step is a trained NN capable of predicting the values of $p_1(W_p)$ and $p_2(P)$ with the required accuracy.

c) Sub-optimization with NN using genetic operators: The final step is an optimization process based on the principles of GA and its genetic operators. In this phase, the trained NN is used to evaluate the penalty values $p_1(W_p)$ and $p_2(P)$ with respect to the initialized coordinates, while the objective function $f(G_s)$ is calculated separately. Together, these components establish the final fitness value. This procedure is repeated until the final generation is reached, and the best estimated configurations are selected to form a portion of the next generation — set to 50% in this study, but adaptable depending on the specific requirements— in the global optimization process. Due to the high computational efficiency of the NN, larger populations and more generations can be explored, allowing the prediction of significantly more optimal solutions.

Integrating these components into the GA enhances the overall performance of the framework, enabling better solutions to be obtained in fewer generations and thereby improving convergence. The basic operation and key components of the NNAGA are illustrated in Figure 1. Additionally, the properties listed in Table 1 are used in this research during the shape optimization process.

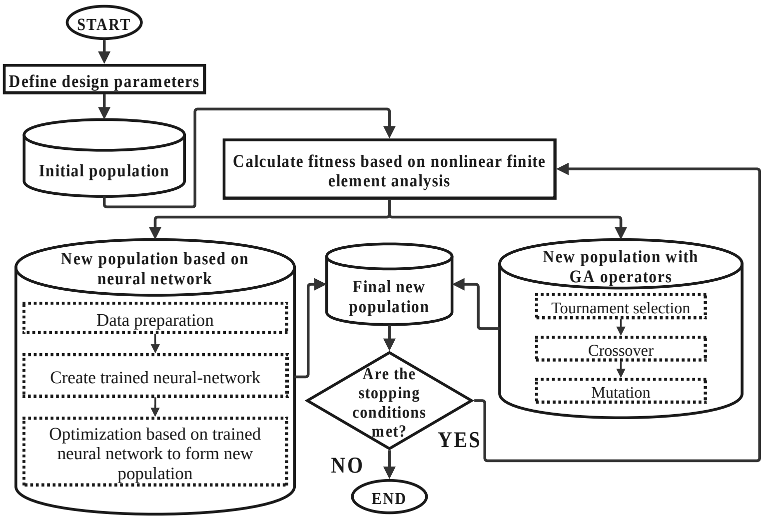

Figure 1: Operation of the developed framework with Neural Network-Assisted Genetic Algorithm (NNAGA).

Algorithm	**Parameter**	**Values**
Genetic Algorithm	Number of generations	20
	Population size	100
	Uniform crossover probability	0.7
	Mutation probability	$0.1 - 0.9$
	Tournament selection size	2
Neural Network	Hidden layers with neuron numbers	$[14, 18, 9]$
	Activation function	Sigmoid
	Learning rate	0.01

Table 1: Utilized Parameters of the GA and the NN.

4 Numerical example

This section presents a numerical example involving a simply supported 33-bar truss structure, as shown in Figure 2, where the range of possible nodal coordinates during the optimization is also illustrated. The nodes are allowed to vary within $\pm 300mm$ in both the horizontal and vertical directions relative to their initial positions. The content is organized into two main parts: first, the introduction of the FE model developed for the analysis; and second, the presentation and discussion of the optimization results. Furthermore, the performance of the NNAGA is evaluated in comparison to the conventional GA, highlighting the advantages of the integrated approach.

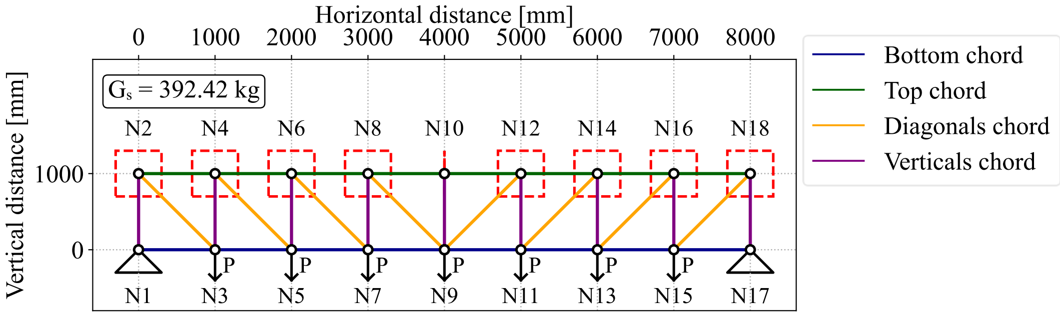

Figure 2: The initial configuration of the numerical example.

4.1 Created finite element model

To carry out the optimization process, the finite element (FE) model was constructed using ABAQUS software. During the simulations Geometrical and Material Nonlinear Analysis (GMNA) was performed to calculate the W_p value with respect to nodal configurations.

The FE model was created using B31 beam elements with a general mesh size of 100mm. The cross-section of all individual bars was uniformly defined as circular hollow sections, with a diameter of 150mm and a wall thickness of 3mm, resulting in a cross-sectional area of $A = 1385.44\text{mm}^2$. The developed FE model is shown in Figure 3, along with the applied boundary and loading conditions, where the magnitude of the nodal forces is $P_0 = 42.4\text{kN}$.

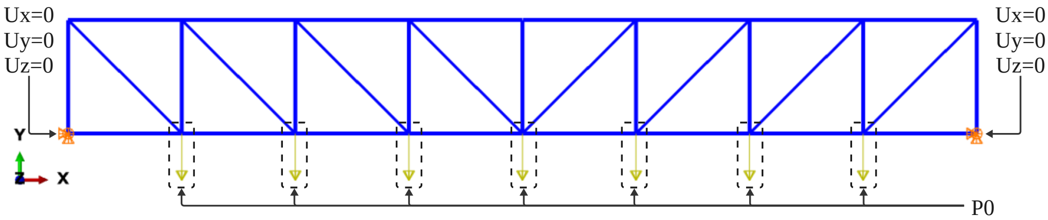

Figure 3: The developed FE model used as the initial configuration for optimization.

During the simulation, an elasto-plastic material model for steel was applied, incorporating an isotropic hardening rule. The material properties used correspond to the nominal values of S235 steel grade, as defined by Eurocode [42]. Considering the density of steel and the applied cross-sectional dimensions, the total weight of the initial configuration was calculated as $G_{s,init} = 392.42\text{kg}$.

After the creation of the FE model the GMNA was conducted and the complementary strain value of residual forces was calculated with respect of the boundary and load conditions, which was $W_{p,init} = 599.66\text{Nmm}$.

4.2 Optimization results and discussion

During the optimization process, the values $W_{p,init}$ and $G_{s,init}$ corresponding to the initial configuration, were used as limiting thresholds, defined as $W_{p0} = W_{p,init}$ and $G_{s,0} = G_{s,init}$. This implies that the primary objective of the optimization is to determine a solution where the plastic deformations remain below $W_{p,init}$, and the total structural weight is less than $G_{s,init}$.

To evaluate the effectiveness of the developed optimization framework, five independent runs were conducted. The results obtained using the NNAGA are presented and compared with those from the conventional GA-based design in Figure 4. Furthermore, the fitness values at the end of the final generation are summarized in Table 2.

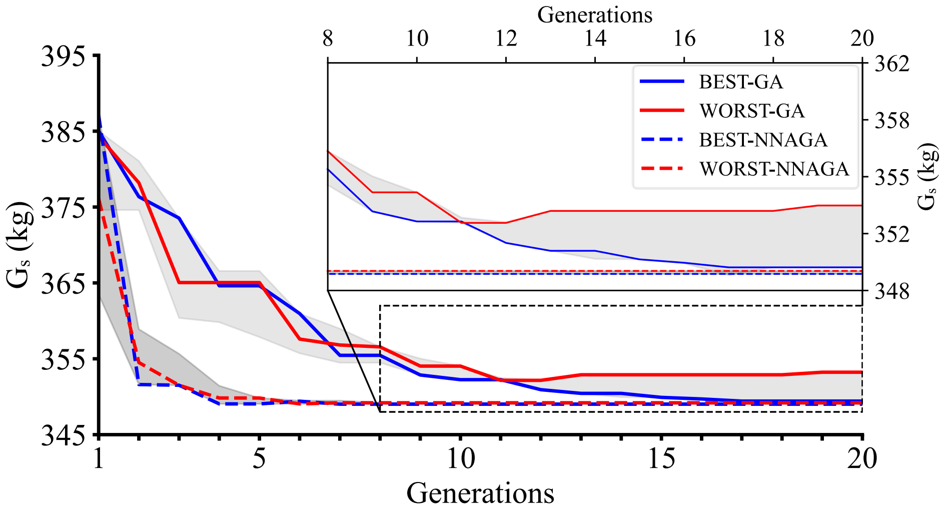

Figure 4: Optimization history of structural weight, highlighting the best and worst cases among 5 independent runs based on fitness values. The shaded region represents the optimization curves of the remaining runs.

Run	GA			NNAGA		
	fitness	G_s (kg)	W_p (Nmm)	*fitness*	G_s (kg)	W_p (Nmm)
1	0.8912	349.71	0.000014	0.8894	349.02	0.000000
2	0.8904	349.42	0.000013	0.8899	349.20	0.000000
3	0.9001	353.23	0.000000	0.8894	349.02	0.000000
4	0.8910	349.66	0.000000	0.8899	349.20	0.000000
5	0.8913	349.78	0.000000	0.8895	349.08	0.000000
Mean	0.8928	350.36	0.000005	0.8896	349.11	0.000000
Std Dev	0.0041	1.61	0.000007	0.0002	0.09	0.000000

Table 2: Summary of optimization results and comparative analysis of GA and NNAGA across five independent runs.

The results presented in Figure 4 and Table 2 indicate that the NNAGA outperforms the conventional GA, especially in terms of optimization convergence. As shown in Figure 4, NNAGA consistently finds an optimal solution across all cases by approximately the $6th$ generation, whereas the GA begins to stabilize only around the $13th$ generation. Furthermore, the fitness values—and consequently the structural weights and corresponding W_p values—are better in every independent run when using NNAGA, with significantly lower standard deviation. These findings suggest that NNAGA can reach the optimal solution in substantially fewer generations, which overall leads to much greater computational efficiency, as fewer configurations need to be evaluated to identify the ideal one.

Additionally, it should be noted that, compared to the initial configuration, the use of the developed framework—whether with GA or NNAGA—results in significant material savings and a reduction in plastic deformations, highlighting the effectiveness of the proposed methodology. These results are summarized in Table 3, and a comparison between the overall best solution obtained using NNAGA and the initial configuration is illustrated in Figure 5. Notably, across all examined cases, the structures with optimized shapes remained entirely within the elastic range by the end of the design process, while achieving approximately 10% material savings.

Configuration	G_s (kg)	$G_s / G_{s,init}$	W_p (Nmm)	$W_p / W_{p,init}$
INITIAL	392.42	100.00%	599.6600	100.00%
BEST - GA	349.42	89.04%	0.000013	0.00%
WORTS - GA	353.23	90.01%	0.000000	0.00%
BEST - NNAGA	349.02	88.94%	0.000000	0.00%
WORST - NNAGA	349.20	88.99%	0.000000	0.00%

Table 3: Comparison between the initial configuration and the optimal solutions.

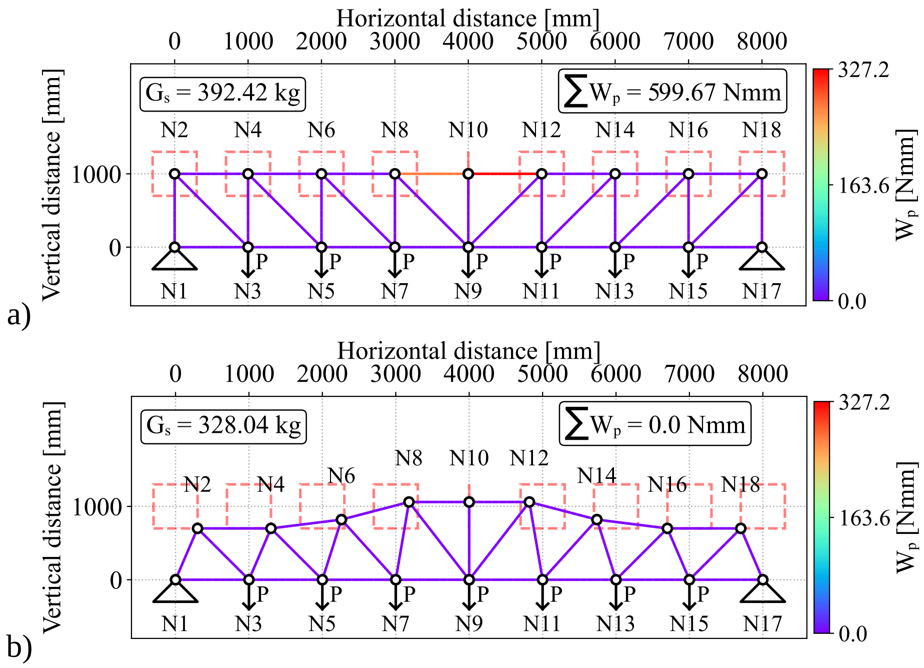

Figure 5: W_p values of a) the initial configuration and b) the overall best solution obtained using NNAGA.

5 Conclusions

In this study, a novel framework is presented for optimizing the shape of elasto-plastic trusses by accounting for large deformation effects through geometrically nonlinear analysis and employing a Neural Network-Assisted Genetic Algorithm (NNAGA) to achieve safe and economically efficient designs. In the proposed methodology, the complementary strain energy of residual forces is calculated to evaluate the plastic performance. This is accomplished by performing Geometrical and Material Nonlinear Analysis (GMNA) for each individual configuration using the Finite Element Method (FEM). To further enhance the efficiency of the optimization process, a Neural Network (NN) is integrated to intelligently learn from the data generated by the Genetic Algorithm (GA), thereby accelerating convergence and improving the quality of the obtained solutions.

The developed framework was validated on a benchmark problem involving a simply supported 33-bar truss structure. The results demonstrated that the proposed approach significantly reduced plastic deformations and achieved notable material savings compared to the initial configuration. Remarkably, the optimized structure remained entirely within the elastic range while achieving an approximate 10% weight reduction solely through shape optimization. Furthermore, the NNAGA exhibited improved convergence behavior and identified superior solutions in fewer generations compared to the conventional GA, contributing to a more computationally efficient optimization process.

The outcomes of this research highlight the potential of the proposed framework and underscore the significance of incorporating elasto-plastic analysis into advanced truss design. By leveraging these techniques, it becomes possible to simultaneously enhance structural safety and economic efficiency by achieving better performance with reduced material usage.

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