Optimal Design of Steel Columns with Axial Load Using Artificial Neural Networks

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Abstract. This study presented a design of experiences approach to solve this problem, whose steps include: 1 generation of experimental design 2 implementation of experimental design 3 construction of response variable model 4 definition of optimization problem 5 solution of optimization problem. The above step 1 to 3 is to create a model of response variables to be as an alternative for structural analysis software, and because the model is a set of regular and simple functions, it can easily define the optimization problem in step 4, and then the optimization problem can be solved with optimization software in step 5. The reason that neural network is employed instead of the traditional regression analysis in step 3 is in structures the relations between internal forces and displacements and section size of members are often nonlinear. The greatest advantage of neural networks is that it is a nonlinear system; hence, it can very precisely build a nonlinear model. In this paper, the optimization of cross section of compressive steel column is employed as the case studies to assess the feasibility of the approach. The results show that this approach can indeed get a more economical design.

Introduction

The purpose of the applications of optimization theory on structural design is mostly to reduce the consumption of engineering materials so as to reduce project cost. In the past, to solve structural optimization problems, it is necessary to combine a structural analysis software and an optimization software. Since structural analysis is the only function considered in the development of most of structural analysis software, they suffer from closeness of system. Therefore, to combine them with an optimization software is difficult.

One possible alternative to solve the difficulty is the design of experiences approach [1], whose steps include.

1. Generation of experimental design: first generate many possible structural design alternatives. Each design alternative consists of many design variables X. For example, a structural design alternative consists of a set of cross section of members.

2. Implementation of experimental design: employ structural analysis software to analyze all structural design alternatives to obtain their internal forces and displacements. They are the response variables Y.

3. Construction of response variable model: employ artificial neural networks [2] to build model Y=f(X) to obtain the relationship functions between the design variables X and the response variables Y.

4. Definition of optimization problem: employ the design variables X and the response variables Y to define the objective function and constraint functions.

5. Solution of optimization problem: employ the optimization software to solve the optimization problem consisting of the objective function and the constraint functions to produce the optimum design variables X*.
The above step 1 to 3 is to create a model of response variables to be as an alternative for structural analysis software, and because the model is a set of regular and simple functions, it can easily define the optimization problem in step 4, and then the optimization problem can be solved with optimization software in step 5.

The reason that artificial neural network is employed instead of the traditional regression analysis in step 3 is in structures the relations between internal forces and displacements and section size of members are often nonlinear. The greatest advantage of artificial neural networks is that it is a nonlinear system; hence, it can very precisely build a nonlinear model. Artificial neural network is a mimic biological neural network information processing system, and has many features and advantages similar to human brain. It uses a large number of simple artificial neurons to mimic the ability of biological neural networks. Artificial neurons are the simple simulation of biological neurons. They receive information from the outside environment or other artificial neurons, and make a very simple operation, and output the results to the external environment or other artificial neurons. Detailed algorithms can be found in the literature [2].

To assess the feasibility of the approach, the optimization of the amount of steel of compressive steel column were employed.

**Neural Network-Based Experimental Design Approach**

This study proposed the neural network-based experimental design approach software called CAFE, its architecture is shown in (Fig.1) This software has three functions:

1. Construction of response variable model: employ artificial neural networks to build predictive model \( Y=f(X) \) to obtain the relationship functions between the design variables \( X \) and the response variables \( Y \).
2. Definition of optimization problem: employ the design variables \( X \) and the response variables \( Y \) to define the objective function and constraint functions.
3. Solving of optimization problem: employ the nonlinear programming optimization techniques to solve the optimization problem consisting of the objective function and the constraint functions to produce the optimum design variables \( X^* \).

Therefore, the last three steps of the above experimental design approach can be implemented on CAFE. In this study, in building neural networks, the following parameters were used: learning cycle = 2000 times; the range of initial weights = 0.3, learning rate = 1.0, learning rate reduction factor = 0.95, learning rate lower limit = 0.1, momentum factor = 0.5, momentum factor reduction factor = 0.95, momentum factor lower limit = 0.1.

**Case Studies**

In general, plastic section design is adopted for most steel columns. Considering ductile capacity, width to thickness ratio \((b/t)\) of cross section of steel column must satisfy the requirements of compact section. In order to increase the range of practical applications of the study, we considered four kinds of sections, namely plastic design section, compact design section, semi-compact design section, section with slender plate element, to increase the available cross sections.

Furthermore, the design engineer can choose common sizes of cross section of steel column, or may choose customized sizes of cross section of steel column. Hence, in this study we employed two data sets, one consisted of domestic common steel H-typed sections, and the other consisted of customized steel H-typed sections generated by random generation of \( H, B, t_w \) and \( t_f \) of steel H-typed sections. Finally, to understand the impact of the size of data set, we also compared the design results based on the data set with 100 data and the data set with 500 data.

**Objective Function and Constraint Functions of Optimization Model**

The mathematical model of minimization of the amount of steel of compressive steel column are listed as follows[3]
1. Objective function

Generally in dealing with structural optimization design, most adopted structural weight minimization as the objective function. In this study, all the columns in the case studies were assumed to have the same length, so to minimize cross-sectional area is the same as to minimize structural weight. Hence, the following objective function is used

\[ \text{Min} A_g \]  

Where, \( A_g \) is the cross-sectional area of steel column.

2. Constraint functions

According to the requirements of the above design code, in the calculation of the ultimate axial compressive strength of column \( P_n \), we must also consider the elastic and inelastic buckling. Therefore, the constraint functions contain the following requirements

\[ \phi P_n \geq P_u \]  

\[ 5 \leq B/2t_f \leq 20 \]  

\[ 20 \leq H/t_w \leq 60 \]  

\[ 1 \leq H/B \leq 2.75 \]  

\[ 1.2 \leq t_f/t_w \leq 2.5 \]

Where \( \phi = 0.85 \); \( P_u \) is the ultimate axial compression; \( B \) is the width of column section; \( t_f \) is the thickness of the flange of column section; \( H \) is the height of column section; \( t_w \) is the thickness of the web of column section.

**Process of the Optimization Design**

The process of minimization of the amount of steel of compressive steel column are listed as follows [3]

1. Generation of experimental design: first generate many possible steel H-typed sections. Each design alternative consists of a set of \( H \times B \times t_w \times t_f \), which are the four design variables \( X_1 \sim X_4 \). Where \( H \) is in the range 100~1020 mm, \( B \) in 22~900 mm, \( t_w \) in 4.5~32 mm, and \( t_f \) in 6~50 mm.

2. Implementation of experimental design: \( Y_1 \) to \( Y_4 \) are \( B/2t_f, H/t_w, H/B, t_f/t_w \), and \( Y_5 \) to \( Y_7 \) are cross-sectional area \( A_g \), compressive strength \( P_n \), and moment of inertia \( I_x \). There are four input variables, seven output variables (response variables).

3. Construction of response variable model: employ artificial neural networks to build model \( Y=f(X) \) to obtain the relationship functions between the design variables \( X \) and the response variables \( Y \). There are four input variables, seven output variables (response variables).

4. Definition of optimization problem: employ the design variables \( X \) and the response variables \( Y \) to define the objective function in in Eq.1 and constraint functions in Eq. 2~6.

5. Solution of optimization problem: employ the optimization software to solve the optimization problem consisting of the objective function and the constraint functions to produce the optimum design variables \( X^* \), that is the optimum set of \( H \times B \times t_w \times t_f \).
Basic Information of the Optimization of Steel Column

In this study, there are two different data sets, the continuous version (customized steel H-typed sections) and the discrete version (domestic common H-typed sections) data sets. The sizes of sections in continuous version data set are randomly generated, and there are 100 data and 500 data versions. The sizes of sections in discrete version data is commonly used H-typed sections in design manual. Five hundred data are selected to form the discrete version data set. In building neural network models, 70% data is randomly chosen as training data, the rest 30% data as test data.

When sorting the commonly used H-typed sections in design manual according to the axial compression strength, and dividing them into four equal parts, under the length of 400 cm, the first to the third quartile of the compressive strength of 375, 772, 1171 tons. So the 800 tons was chosen as the external axial compressive loads in the case studies.

The basic data of steel column optimization design are as follows: the nominal yield stress $F_y = 3.5$ t/cm$^2$, residual stresses $F_r = 1.16$ t/cm$^2$, Young's modulus $E = 2100$ t/cm$^2$, shear modulus $G = 810$ t/cm$^2$, material unit weight $\rho = 7.849$ t/m$^3$, effective length factor on x-plane $k_x = 1.65$, effective length factor on y-plane $k_y = 0.75$, length $L = 400$ cm.

In this study, using the three data sets, the 100 data and the 500 data continuous version data sets and discrete version data set, three neural network predictive models were built. The predicted values of the response variables using neural network models are called "predictive value." The computed values of the response variables using design code formula are called "actual value." The study will compare the prediction accuracy of the two continuous version data sets to evaluate the impact of the size of the data sets.

After the optimization design process, we obtained the following optimized results:

1. Table 1 shows the design results. Using the data set with 100 data, the optimum section size is H849×432×11×24 with 295.5 cm$^2$ area; using the data set with 500 data, the optimum section size is H550×480×11×24 with 285.6 cm$^2$ area; using the discrete data set, the optimum section size is H700×400×14×25 with 291 cm$^2$ area. It can be seen that using the data set with 500 data can obtain the most economical section size with the minimum cross-sectional area.

2. Table 2 lists the actual values and the predicted values of the response variables, which also shows the larger the data set, the more accurate the forecast.

<table>
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<th>continuous version data set with 500 data</th>
<th>discrete version data set</th>
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Table 1. The design results.

Table 2. The predicted and actual values.
### Summary

According to the results of the three case studies, the following conclusions can be obtained:

1. In the axial force of 800 tons, the approach can find the optimum steel column section designs which conform to design specifications.
2. The data set with 100 data is insufficient to establish accurate predictive models; while the data set with 500 data is sufficient.
3. The optimum cross-sections obtained with the neural network built based on the continuous version data set with 500 data are more economical than those based on the discrete version data set with 500 data.

The conclusions show that it is feasible to replace the traditional approach directly coupling mechanical analysis model and optimization software with the experimental design approach. In the future we will extend this approach to replace the traditional approach directly coupling complex finite element method software and optimization software with the experimental design approach for the optimum design of complex structures.

![Architecture of CAFE](image_url)

**Figure 1.** Architecture of CAFE: the software based on experimental design approach using neural networks.
Reference