Research Article

Data-Driven Decision-Making in the Design Optimization of Thin-Walled Steel Perforated Sections: A Case Study

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The rack columns have so distinctive characteristics in their design, which have regular perforations to facilitate installation of the rack system that it is more difficult to be analyzed with traditional cold-formed steel structures design theory or standards. The emergence of industrial “big-data” has created better innovative thinking for those working in various fields including science, engineering, and business. The main contribution of this paper lies in that, with engineering data from finite element simulation and physical test, a novel data-driven model (DDM) using artificial neural network technology is proposed for optimization design of thin-walled steel specific perforated members. The data-driven model based on machine learning is able to provide a more effective help for decision-making of innovative design in steel members. The results of the case study indicate that compared with the traditional finite element simulation and physical test, the DDM for the solving the hard problem of complicated steel perforated column design seems to be very promising.

1. Introduction

The advances in the logistic and storage fields have been promoting the wide application of the automated storage and retrieval system (AS/RS) in China. Acting as critical infrastructure for AS/RS, structural design for pallet rack needs elaborate decision-making between structural systems and a variety of steel members in such a way that the stability behaves as intended by the designer and satisfies the constraints imposed by capital investment, environment, and so on. In virtue of the high strength to weight ratio as well as convenience of fabrication and assembly, thin-walled steel is widely used in many fields such as industrial storage racks, civil engineering, bridges, transmission towers, and others [1]. The diversity of wide products, with many dissimilarities of shapes, sizes, and usages, are manufactured by cold forming techniques including folding and rolling and so on. These techniques evidently improve the tensile strength and yield strength but in the meantime also reduce the ductility of thin-walled steel member. Especially the properties of the

corners within thin-walled steel sections are very different from those of the planar steel sheet, bar, or strip after cold forming. Moreover, the thin-walled steel members often buckle locally at some stress level lower in comparison with the yield strength itself when they are under tremendous compression. Up to now, the ultimate load calculations within thin-walled columns design can be obtained by some specific computer programs such as CUFSM [2] and Thin-Wall [3], using the finite strip method (FSM) and GBTUL [4], applying the generalized beam theory (GBT). The direct strength method can be also applied very effectively in other specific programs [5]. However, unlike traditional civil buildings or commercial facilities, the main load-bearing members in storage racks such as columns usually comprise regular arrays of perforations in length direction, which enable beams to be hung by connectors at adjustable heights along with the bracings to constitute the huge three-dimensional framework (Figure 1). The ultimate load capacity of rack column can vary with perforation size, shape, position, and orientation [6, 7]. The stability behavior is one

FIGURE 1: (a) Massive automated storage and retrieval system (AS/RS). (b) Arrays of perforations of columns.

of the most prime importance for decision-making of thin-walled steel racks design. Under the influence of continuous perforations, the buckling behavior and load capacity of column may vary so fairly that the various perforations section makes the design procedure of those thin-walled steel columns more complex. Unfortunately, these methods and programs aforementioned cannot be directly used to the perforated steel members because GBT and FSM are essentially 2D theories, but the analysis of these thin-walled perforated sections is a typical 3D problem [8]. The finite element method (FEM) can be naturally used [9], but the computational cost is too expensive to be widely applied in engineering design. In the past years, many investigations [10, 11] were devoted to the study of holes and its arrangement on the ultimate load of rack uprights; however, it has not been achieved in the universally accepted analytical design method for industrial storage racks [12]. For this reason, the current steel member design of pallet rack still mainly depends on physical tests prescribed by specific standards. The increasing demand of cold-formed thin-walled steel in modern industry needs to explore more novel methods of design decision on ultimate load of thin-walled perforated steel member.

Within the design process, the reasoning inherent is to be implemented on different levels with different degrees of uncertainty, abstraction, and impact on product decisions for the elaborate balance between the product quality and manufacturing cost. Actually, the stability analysis for the high-rise steel storage rack structures is becoming even more important, although it has been used for several decades. Furthermore, with advances in various virtual design tools, many engineers and producers have been migrating from physical testing to simulation-based design so that a large number of engineering analytical data have been accumulated so far. The proliferation of industrial “big-data” has been creating many exciting opportunities for those working in various fields such as science, engineering, and business. It has been gradually realized that not only those data from engineering analysis can be used for the product development but also they have the potential to provide

insight and knowledge for the designer to improve the product quality itself. Beyond the specific challenges, technologies and tools have been developed to support decision-making in each phase of product design with relative techniques from the so-called “big data.” In recent years, the machine learning (ML) and data mining (DM) from industrial big data have been rapidly developed as a new discipline in computer science and engineering application [13, 14]. From the perspective of engineering application, the ML and DM focus on analysis and discovery of the potential pattern of the production process and can realize precise prediction of complex engineering problems. Of course, it can also be used to provide a more effective solution for decision-making of enterprises’ innovative design. Among machine learning approaches, artificial neural network (ANN) algorithms have a significant role in predictive modeling because they can be easily utilized to establish the component which learns from existing engineering data in order to make predictions on new engineering data [15].

In constructional steel field, the main contribution of our study is to present an alternative data-driven model using ANNs to overcome some inherent difficulties associated with the design load of perforated steel members and make the optimal design decision of the thin-walled column section with the combination of mechanical performance and fabricating cost factors. In contrast with existing references, the obvious distinctions of our report lie in that the finite element simulation data based on the physical test that are utilized to train BP artificial neural networks in consideration of the perforated effect and uncertainty assessment, and results have been taken comparisons with those of the traditional FEM. The relative model, experiments, and research method are discussed in this paper.

2. Proposed Model Framework

Given conflicting factors (e.g., socioeconomic, safety, environmental, and among others), people often have to make

judgments based on their experience, knowledge, or outcomes of costs-benefits/risk analysis. For a decision maker of the high-rise steel storage rack, achieving the stability goals while meeting the constraints of the production cost is one of the most essential concerns. Up to now, the models available to solve the various design decision problems on steel member can be categorized into two main types: physical-based models and data-driven models. On the one hand, the physical based models are usually considered to be complex, since they require (i) use of knowledge on the physics of interrelationships among various column sectors parameters and the ultimate load, and (ii) adequate data on various tests for model calibration. On the other hand, data-driven models do not consider the physics of the buckling processes but can be effective when large data sets are available on predicting and reasonable number of predictors. The artificial neural networks (ANNs) are one of most widely used data-driven methods based on machine learning. This method has the ability to handle noisy data and thus takes advantage over conventional methods of real-world scenario, where the perforated steel member of compression is typical nonlinear physical relationships underlying various buckling processes that are seemingly not fully understood.

Considering these salient features of ANN, there is a proposed ANN-based data-driven model (DDM) on thin-walled steel perforated member (Figure 2). The model framework is mainly made of four modules, that is, input and output modules, user interface, machine learning approaches, and data acquisition. Being the most critical index on stability design from engineering point of view, the ultimate load ought to be selected as the output of intelligent decision model. The other output is the price of column production that is directly obtained by regular computation. Associated with the mechanical performance of rack column, those important design parameters such as the perforated section, material properties, and fabricating imperfection are chosen as the inputs of DDM. The data acquisition is designed for collecting and transforming the data from the finite element simulations and physical experiments into engineering database. Because the column physical experiments are relatively expensive and real dataset is usually limited in number, and the finite element simulation is employed to expand engineering data as ANN training required in this paper. The user interface is mainly responsible for kind interactive operation with the model, such as feature extraction, model training, parameter optimization, and so on. The machine learning approach is essentially an ANN-based ultimate load prediction toolkit, which can be applied to automatically train the data models and make intelligent design decision in terms of the real thin-walled perforated column inputs. The DDM employs an intelligent decision technique simulating how structure engineer routinely solves problem. When a new AS/RS project is developed, in most cases, the structure engineers firstly need referring to some similar solutions within the existing engineering projects and then obtain a series of similar design parameters of thin-walled steel members including section, material, and others. By means of the ANN-based predictive toolkit, an accurate mechanics

FIGURE 2: Framework of the proposed data-driven design decision based on prediction and optimization of column.

performance of rack column can be predicted very quickly before the new columns are manufactured. These steps usually need continual iterating until some conflicting conditions such as performance and cost can be satisfied at the same time. As a result, the best design decision can be made, and then, the column section parameters optimized. Unlike the existing programs and methods [2–5], the novelties of data-driven model consist the following:

- (i) Encapsulating a great deal of knowledge in a very efficient manner has the capability of updating system knowledge through continuous self-learning.
- (ii) Have robust reasoning mechanism oriented to optimize section parameters according to computer simulation.
- (iii) Take account of factors that are not easily quantifiable (nonnumeric) such as ease of construction, failure mode, and availability, effectively avoiding rule collision as well as trouble from explicit knowledge acquirement.

3. Stub Column Tests

In this paper, the coupon tests of stub column had been performed to synthetically evaluate ultimate load and its strength of these members under consideration of perforations, cold forming processes, various buckling, and its interactions on the basis of EN15512 [16]. The length of specimens is fully satisfied by the code requirements; that is, (1) at the midway between two sets of perforations, it comprises at least five pitches of the perforations. The cap and base plates are welded to each end of the stub upright; (2) the length of specimens is about three times the greatest

FIGURE 3: The experiment setup and supporting system of EN15512 [16].

width of the stub section (without intermediate stiffeners). The end-devices, at both ends, are made of pressure pads of 30 mm thick with around 5 mm indentation and 40 mm diameter ball bearing. The coupon sample is fully grasped at both ends when the tests started. The goal of these experiments was to obtain the precise tensile yield and ultimate load for each thin-walled steel column specimen so that these real engineering data are used to verify the FE model and ANN model. The experiment setup and supporting system are shown in Figure 3. The load was continuously increased until the specimen has buckled and accepted no more load. This load was recorded as the ultimate failure load. The characteristic failure loads (i.e., the ultimate load) were based on a series of tests with the same load position. Nine series of open thin-wall steel sections (Figure 4) chosen as stub columns in pallet racking have been tested and analyzed. The samples parameters of the short column mechanical performance compression test are shown in Table 1 and Figure 5. Dimensions range of upright specimens is relatively wide: flange of 50~145 mm, web of 45~120 mm, and thickness of 1.8~2.5 mm. Nine representative column cross section series selected for the specimen preparation are M45-43, M60-55, M75-58, M90A-65, M90B-78, M100A-90, M100B-100, M100C-130, and M120A-95 which covers the main range of industry manufacturing and application. Among them, five sections have only intermediate stiffener, two sections have edge and intermediate stiffeners, and other sections have none. Total 30 data from different stub columns compression experiments were collected from the Shanghai Jingxing Logistic Equipment Engineering Co., Ltd., China.

Here, the selection of stub columns takes the size of the web, the change of the flange, and reinforcement into consideration to make the DDM much more adaptable. The distribution of tested column sections is illustrated as Figure 6. All experimental data are elaborately divided into two classes

among which 12 data sets are used to verify the finite element model, and the rest are used to make the comparisons with the data-driven model and finite element model.

4. Finite Element Simulation

4.1. Establishment of Geometric Model. The finite element (FE) method has generally accepted to be a very powerful and effective tool for analysis of perforated members and predicting their strength and behavior [9, 10]. In order to develop a high-precision finite element model, however, it is necessary to identify all possible physical actions involved within the structural system under consideration. Referring EN15512 [16], an elaborate finite element model in our study has been built with the professional ANSYS software [17]. Firstly, the 3D models are established based on the actual numerical value of the tested samples using Solidwork software. It is noticed that the cross section and the hole setting are not simplified to ensure the accuracy of the finite element model (Figure 7). After importing the FE model, the element type has been set as SOLID187 which is a high-order solid structural element, including 10 nodes in 3D. The element type SOLID45 is also carefully applied for the load plates modeling. The eight-node three-dimensional solid element with three free degrees per node is often used for linear and nonlinear analysis in the same way.

4.2. Material Properties and Mesh Generation. The materials are setting with nonlinear steel for subsequent buckling analysis by the ANSYS Workbench with Structure Steel NL. Steel yield strength and tensile strength are referred to the Chinese standard GB 50017 2003 [18], where the elastic modulus is 200 GPa, the Poisson ratio is 0.3, and the density is 7850 kg/m³.

Meshing is the basis of finite element analysis. Reasonable meshing can reduce the use of computer memory, and the results were more accurate. Compared to tetrahedral (TET) meshes, hexahedral (HEX) meshes have higher precision and less calculate time. Therefore, HEX dominant has been in the mesh method, the mesh size, smoothness, and other factors are adjusted at the same time. Considering the accuracy of calculation and memory usage, the relevance was adjusted to 50. The imported mesh models are shown in Figure 8.

4.3. Boundary Condition and Loading. Within the column experiments, the test specimen was mounted with the centroid of its gross cross section positioned centrally in the testing machine with one loading platen free to rotate in order to take up any lack of alignment of the end plates of the specimen. In order to simulate the compression test, on a central node of the outer face of two load plates, the displacements shall be properly specified; that is, the line located by these two nodes is the so-called load line (Figure 9). All node displacements of the bottom plate have been set up to zero, and the transversal displacements of the node at the top plate have also been set up to zero. The axial displacement of the load line is gradually increased step by step until the stub

FIGURE 4: Nine series specimen for column tests.

TABLE 1: Dimension of stub test samples (parameters are shown in Figure 5).

Parameter type	a (mm)	b (mm)	c (mm)	L (mm)	d (mm)	e (mm)	f (mm)
M45	45	43	12	300	25	110	125
M60	60	55	12	350	41.8	170	125
M75	75	58	12	400	40.4	170	125
M90A	90	65	12	400	37.1	170	125
M90B	90	78	12	400	33	170	125
M100A	100	90	12	400	25.8	170	125
M100B	100	100	12	400	22.9	170	150
M100C	100	130	12	400	20	170	170
M120A	120	95	12	400	22.5	170	140

can be no longer in force. The controlled displacement method can be applied to simulate the physical test process of ultimate load on the upper plate of the stub column. The displacement is added in continuous increments until it obviously begins to decrease or keep unchanged within a span of time window. At that moment, the maximum load in the stub can be considered the failure force, that is, the ultimate load.

4.4. FE Model Validation. The physical tests for 12 tested stub columns were utilized to calibrate FE simulation models. For example, Figure 10 presents the characteristic failure modes of M90 column compression for experimentally tested and numerically simulated specimens. Obviously, it can be observed that there are good agreements between the modes of the buckling in experiments and analyzed by numerical simulations. It also can be observed in Table 2 that all finite element results were higher than the experimental ones. The reasons for this could be that the geometrical imperfection, residual stress, and nonlinear effects of materials are not fully considered in the finite element model. However, the deviations of FEM simulation have been controlled, not larger than 10% of the real experimental data (Table 2). Therefore, it is concluded that from the point of view of engineering application, the FE

model is able to accurately simulate the experimental tests. The additional 60 data (Table 3) from simulation of different stub columns are obtained by the finite element method based on the physical test, which have been supplementary data for the data-driven model based on ANN.

5. ANN Model Training

In the past years, the application of ANNs has rapidly grown in popularity. The neural networks represent a novel and modern technical conception that can provide solutions in problems for which ordinary algorithms, mathematics, and methodologies are unable to find an acceptable and satisfactory solution [15]. These problems are generally so sophisticated that some of the related mechanisms could not be fully understood by the researchers so far. The internal detailed architecture of ANN for prediction of the ultimate load of thin-walled perforated steel sections is shown in Figure 11.

5.1. Basic Steps of Model Design. The design of the ordinary ANN model may be divided into five steps as follows:

- (i) Step 1: Initialization. Setting the ownership value to random arbitrarily small
- (ii) Step 2: According to the research content, determining input variables and expected output of variables
- (iii) Step 3: Recording the output value which is calculated by passing the function step by step and the final output value
- (iv) Step 4: Adjusting weight. Use recursive methods to adjust weights sequentially from the output node to the intermediate hidden layer.
- (v) Step 5: Returning to the second step and repeating the operation to reduce the error of the output layer.

5.2. The Determination of the Hidden Layers. The determination of the hidden layer in the BP neural network

FIGURE 5: Parameters of column test.

model is the key step of modeling which predicts the reliability of steel members. At present, the determination of network parameters (hidden layer number and hidden layer number of neurons) is uncertain. However, in the light of

FIGURE 6: The test number of column.

Bishop's report [19], more than one hidden layer is usually not necessary, and the ANN architectures for thin-walled steel design have only one hidden layer. The ANN is trained using a back-propagation algorithm with gradient descent and momentum terms. The number of hidden layers is often related to the number of training samples, the number of neurons in the input layer, and the number of neurons in the output layer in engineering. In literature [15], the node number of hidden layers was obtained as

$$s = \sqrt{0.43mn + 0.12n^2 + 2.54m + 0.77n + 0.35} + 0.51, \quad (1)$$

where m is the number of neurons in the input layer and n is the number of neurons in the output layer.

5.3. The Relational Mapping of Predictive Model Data. On the basis of current reports [6, 7], there were nine input neurons representation of nine different perforated sections parameters and one output neuron, that is, ultimate load, all listed in Table 4.

The input feature indicators are selected as follows.

5.3.1. Geometric Parameter. The influence of the column length (CL) (L in Figure 5) and the web width (WW) was obvious to the ultimate loading of the column. So the CL and the WW are considered as input variables; based on the parameter sensitivity analysis in literature [19, 20], three parameters which most sensitive (column thickness (CT), opening size (OS), and the flange width (FW)) were put into the forecasting model as input variables.

5.3.2. Structure of Hole. In order to eliminate the effect of the difference on the structure of hole, in this paper, the ratio of the hole area (RHA) was one of the input variables of the prediction model. The equation of RHA is as follows (the formula corresponds to Figure 12):

$$\eta = \frac{S_1 \times n_1 + S_2 \times n_2}{h \times w} \times 100\%, \quad (2)$$

where w is the web width (WW), h is the column length (CL), S_1 is the proportion of the hole shape A, S_2 is the proportion of the hole shape B, n_1 is the number of the hole shape A, and n_2 is the number of the hole shape B.

FIGURE 7: 3D models of stub column.

FIGURE 8: Mesh of the FE model on stub column.

5.3.3. Bending and Right Angles of Section. GB 50017 2003 [18] is the principle for the design of the storage racking system which considers the number of angles of 90 degrees in the cross section as an essential parameter. The bending

(bending number (BN)) and right angle (right angle number (RAN)) of the column section have influence on prediction results that determined them as the parameters of input variables.

5.3.4. Reinforcement. Reinforcement is an effective structural feature to improve the strength of column. The cross section shape of the column series is different, and the reinforcement number (RN) directly affects the ultimate loading of the column (ULC). The dimensional details of the columns are shown in Figure 13.

5.4. The Training Process of the Model. Before being fed into ANN, all the data have to be normalized by a preprocessing way where the data are converted in the range $(-1, 1)$. Under feed-forward neural network architecture, each neuron in the hidden layer is responsible for connection of all the neurons in the next and previous layer. Here, the neural network is trained with node number of hidden layers near

FIGURE 9: Constraint and load setting of the FE model on stub column.

FIGURE 10: The comparison between FEM simulation and physical test (M90 column).

TABLE 2: Comparison among the real measured values and finite element numerical values.

Column type	Measure (N)	FEM (N)	Absolute error (%)
M45-1.5	48735.72	49856.30	2.31
M60-1.8	79771.43	80079.38	0.39
M60-2	107829.81	116348.70	7.90
M75-1.8	120201.30	120906.59	0.58
M75-2	126332.15	133166.10	5.41
M90A-1.8	131635.70	132295.27	0.51
M90B-2	145770.64	156700.50	7.50
M100A-2	184553.71	189905.90	2.91
M100B-2.5	219416.60	220570.64	0.54
M100C-3	341267.70	343081.97	0.53
M120A-2.5	219843.50	238998.70	8.71
M120B-3.5	414820.20	417018.34	0.53
Mean relative error (%)		3.10	
Correlation coefficient, R		0.97	
Proportion of cases with over 5% error		4/12	

In M45-1.5, M45 is the column type, and 1.5 is thickness of the tested stub column.

the one suggested by (1), and finally, nine are found to be most suitable for these specific data sets.

The training function, “trainlm,” has been utilized with the MATLAB ANN toolbox to realize the training of these models. The transformation function of the output layer is “purelin,” and hidden neuron function was “tansig,” which can be obtained from the same ANN toolbox of the MATLAB software [21]. The learning rate η was set from 0.01 to 0.07, which can speed up the convergence of training function on the condition of accepted training precision (Figure 14).

5.5. Uncertainty Assessment. Network training will be automatically terminated if the accepted prediction accuracy of these models such as for the corresponding deviation is not more than 5% between the expected values and the real values. However, with the double purpose of solving the matter of choosing the data to be used in the training and testing phases, a so-called bootstrap resampling method need to be used for uncertainty analysis in statistics and model calibration, by considering an ensemble of ANNs built on different data sets that are sampled with replacement (bootstrapped) from the original one. An obvious merit of this approach is that it provides confidence intervals for a given model output, without making any model assumption (e.g., normality). Here, the entire available data set of N input/output patterns were divided into training, validation, and test data sets equal to 60, 12, and 18 data, respectively. From each bootstrap data set (e.g., resampling times $B = 60$ in this work), a bootstrapped prediction model is trained while the model output of interest can be calculated. Different bootstrap data sets give rise to a distribution of regression functions, and an example of the probability density function (PDF) of the data-driven model output was demonstrated in this paper (Figure 15). So, the model uncertainty of the estimates from the ANNs can be quantified in terms of $(100 \times (1 - 0.05)\%)$ confidence intervals of the obtained model output PDF by the bootstrap algorithm (Figure 16), where

TABLE 3

Column type	Parameter									
	WW (mm)	CT (mm)	FW (mm)	OS (mm)	CL (mm)	RHA (%)	BN	RAN	RN	ULC (N)
M45-1.5	45	1.5	45	25	300	18.205	8	4	0	48458.90
M45-1.5	45	1.5	45	25	300	16.472	8	4	0	49012.59
M45-1.5	45	1.5	45	25	300	15.605	8	4	0	49246.13
M60-1.8	60	1.8	55	34	350	16.525	8	4	0	79349.60
M60-1.8	60	1.8	55	34	350	14.951	8	4	0	80309.17
M60-1.8	60	1.8	55	34	350	14.164	8	4	0	80579.36
M60-2	60	2.0	55	34	350	16.525	8	4	0	107308.45
M60-2	60	2.0	55	34	350	14.951	8	4	0	108429.67
M60-2	60	2.0	55	34	350	14.164	8	4	0	108884.60
M75-1.8	75	1.8	58	45	400	14.222	12	4	1	120201.34
M75-1.8	75	1.8	58	45	400	12.868	12	4	1	121653.31
M75-1.8	75	1.8	58	45	400	12.190	12	4	1	122051.82
M75-2	75	2.0	58	45	400	14.222	12	4	1	125674.21
M75-2	75	2.0	58	45	400	12.868	12	4	1	127122.11
M75-2	75	2.0	58	45	400	12.190	12	4	1	127736.96
M90A-1.8	90	1.8	65	50	400	11.852	12	4	1	131635.78
M90A-1.8	90	1.8	65	50	400	10.723	12	4	1	132952.78
M90A-1.8	90	1.8	65	50	400	10.159	12	4	1	133487.52
M90A-2	90	2.0	65	50	400	11.287	12	4	1	137228.00
M90A-2	90	2.0	65	50	400	11.852	12	4	1	136535.41
M90A-2	90	2.0	65	50	400	10.723	12	4	1	137893.69
M90A-2	90	1.8	78	50	400	11.287	12	4	1	145158.87
M90B-1.8	90	1.8	78	50	400	11.852	12	4	1	144433.37
M90B-1.8	90	1.8	78	50	400	10.723	12	4	1	145882.63
M90B-1.8	90	1.8	78	50	400	10.159	12	4	1	146606.83
M90B-1.8	90	2.0	78	50	400	11.287	12	4	1	145770.64
M90B-2	90	2.0	78	50	400	11.852	12	4	1	145100.68
M90B-2	90	2.0	78	50	400	10.723	12	4	1	146512.32
M90B-2	90	2.0	78	50	400	10.159	12	4	1	147241.47
M100A-2	100	2.0	90	52	400	10.667	20	4	3	183607.50
M100A-2	100	2.0	90	52	400	9.651	20	4	3	185707.72
M100A-2	100	2.0	90	52	400	9.143	20	4	3	186247.73
M100A-2.5	100	2.5	90	52	400	10.667	20	4	3	205633.26
M100A-2.5	100	2.5	90	52	400	9.651	20	4	3	207815.04
M100A-2.5	100	2.5	90	52	400	9.143	20	4	3	208788.40
M100A-2.5	100	2.0	100	52	400	10.159	12	4	1	160872.36
M100B-2	100	2.0	100	52	400	10.667	12	4	1	160047.57
M100B-2	100	2.0	100	52	400	9.651	12	4	1	161711.47
M100B-2	100	2.0	100	52	400	9.143	12	4	1	162635.84
M100B-2	100	2.5	100	52	400	10.159	12	4	1	220570.64
M100B-2.5	100	2.5	100	52	400	10.667	12	4	1	219416.61
M100B-2.5	100	2.5	100	52	400	9.651	12	4	1	221593.87
M100B-2.5	100	2.5	100	52	400	9.143	12	4	1	222748.78
M100C-2	100	2.0	130	52	500	10.159	20	4	3	198040.25
M100C-2	100	2.0	130	52	500	10.667	20	4	3	197057.77
M100C-2	100	2.0	130	52	500	9.651	20	4	3	198989.66
M100C-2	100	2.0	130	52	500	9.143	20	4	3	199955.70
M100C-3	100	3.0	130	52	500	10.667	20	4	3	341267.75
M100C-3	100	3.0	130	52	500	9.651	20	4	3	344931.18
M100C-3	100	3.0	130	52	500	9.143	20	4	3	346865.14
M120A-2.5	120	2.5	95	76	500	8.466	12	4	1	221090.23
M120A-2.5	120	2.5	95	76	500	8.042	12	4	1	222232.38
M120A-2.5	120	2.5	95	76	500	7.619	12	4	1	223289.19
M120A-3	120	3.0	95	76	500	8.466	12	4	1	270660.52
M120A-3	120	3.0	95	76	500	8.889	12	4	1	269336.45
M120A-3	120	3.0	95	76	500	8.042	12	4	1	272240.91
M120A-3	120	3.0	95	76	500	7.619	12	4	1	273437.50
M120B-3.5	120	3.5	150	76	500	8.889	20	4	3	414820.24
M120B-3.5	120	3.5	150	76	500	8.042	20	4	3	419345.72
M120B-3.5	120	3.5	150	76	500	7.619	20	4	3	421089.69

FIGURE 11: ANN architecture.

TABLE 4: Mapping relation of input and output indicators of the prediction model.

Input index	WW	CT	FW	OS	CL	RHA	BN	RAN	RN
Output index									ULC

FIGURE 12: Holes' pass and distribution of M90A series column.

FIGURE 13: Section details of column.

the edges of the box represent the 25th and 75th percentiles and those of the whiskers the 99.3 coverage if the data are normally distributed. The estimates of the best ANN (*dots) and of the bootstrap ensemble of ANNs (red lines) are reported together with the FEM output (plus signs). And these points (represented by a plus sign) are outliers since they are beyond the edges of the box. The presence of

FIGURE 14: The iterative process of predictive model.

FIGURE 15: PDF curve of the model output.

outliers illustrates that some of the bootstrapped networks could not be well trained because of (i) inefficient calibration of the ANN weights during training (e.g., the back-propagation algorithm maybe falls into a local optimum), or (ii) “unhealthy” configurations of the validation data

FIGURE 16: Confidence intervals of the ultimate load.

TABLE 5: Comparison among the real measured values, predicted values, and finite element numerical values.

Column type	Measure (N)	Predict (N)	Relative error (%)	FEM (N)	Relative error (%)
M45-1.5	48385.62	48429.20	0.09	49856.37	3.04
M60-1.8	79136.73	83558.23	5.59	80079.43	1.19
M60-2	107142.80	104077.64	2.86	116348.72	8.59
M75-1.8	120057.01	115392.37	3.88	120201.36	0.12
M75-2	125481.44	126375.42	0.71	133166.13	6.12
M90A-1.8	131412.35	131070.89	0.26	131635.72	0.17
M90A-2	136364.28	140316.60	2.89	144199.20	5.75
M90B-1.8	144144.65	135171.32	6.22	145158.93	0.70
M90B-2	144746.99	146277.65	1.06	156700.55	8.26
M100A-2	183358.52	180049.49	1.80	189905.92	3.57
M100A-2.5	205056.90	207739.80	1.31	206744.95	0.82
M100B-2	159740.04	162860.88	1.95	167594.50	4.92
M100B-2.5	219082.27	218138.34	0.43	219416.63	0.15
M100C-2	196641.13	198992.22	1.19	207407.37	5.48
M100C-3	340630.69	342183.74	0.45	341267.72	0.19
M120A-2.5	219349.62	217817.09	0.69	238998.79	8.96
M120A-3	268689.38	271741.82	1.13	270660.52	0.73
M120B-3.5	413894.01	417135.66	0.78	414820.20	0.22
Mean relative error (%)		1.69		3.28	
Correlation coefficient, R		0.99		0.97	
Cases with over 5% error		2		6	

sets owing to random sampling with replacement implied by the bootstrap such as too large number of repeated samples. The bootstrap resampling method-based operative steps to identify the confidence intervals of the distribution of the regression error are detailed in papers [22, 23].

5.6. Result and Discussion. The final results are listed in Table 5, where “Measure,” “Predict,” and “FEM” refer to the

(a)

(b)

FIGURE 17: (a) The ROC curve between real measurement and ANN prediction. (b) The ROC curve between real measurement and FEM simulation.

TABLE 6: Centerline and weight of the sample.

Parameter	Number			
	1	2	3	4
WW (mm)	90	90	90	90
CT (mm)	2.0	2.0	1.8	1.8
FW (mm)	65.0	60.0	72.0	72.5
OS (mm)	50	50	52	45
CL (mm)	400	400	400	400
RHA (%)	11.53	10.92	12.46	12.96
BN	12	20	12	12
RAN	4	4	4	4
RN	1	3	1	1
UCL (N)	136849.52	139997.03	134796.78	133987.94
Fabrication cost	Low	High	Low	Low

FIGURE 18: Sections of sample (unit: mm).

measured values, the predicted values, and finite element numerical values, respectively. Statistical parameters such as the mean absolute error % and the correlation coefficient R between the expected and real values are used to judge the predictive power of the data-driven models. It is evident that the accuracy of the predictive models is relatively high in all $R > 95\%$, while the ANN model in the mean absolute error and the ratio of the cases with more than 5% error is lower than the FE model. On the contrary, in order to evaluate how good the models and its generalization are made from the ANN model and FEM more clearly, the receiver operating characteristic (ROC) curves are applied to evaluating the proportion of correctly predicted cases as the maximum relative error increases within a prespecified range. A baseline named “normal” was built by the ROC curve (Figure 17) quantized as 1 when the relative error between the observed value is within the range of 5%, and another baseline named “anomaly” is quantized as 1 when the observed value is outside the reference range. The ROC curve evaluating the proportion of correctly predicted cases as the maximum relative error increases within a prespecified range. In this case, it can prove that the ANN prediction is more precise than the FEM simulation for the AUC (area under the ROC curve) of the former is 0.06 than the latter. So, the data-driven models can be more suitable to the

accurate load prediction during the perforated steel member design.

6. Optimization of Design Decision-Making

Considering the social economy, safety, environmental protection, high quality, and other opposing factors, mankind usually makes decisions based on their experience, knowledge, or outcomes of costs-benefits/risk analysis. However, some opposing multiple goals or criteria in decision-making processes may need some optimization because the simple solutions were resisted [24]. Similarly, in the design of racks with thin-walled perforated steel, the engineering projects often involve multiple goals in practice. For example, manufacturers and suppliers are demanding less raw material and more economic efficiency, while consent building authorities require the shelves to have safety coefficients that meet the relevant design code; and end-users hope that the rack will have higher utilization rate for better economic efficiency. These design stakeholders have cross-lights on the appropriate design option within conflicting design decision criteria of safety, economy, and societal considerations [25]. The factors that influence decisions have multiple attributes (e.g., decision goals, diverse criteria, and scope of application), whereby a decision-

TABLE 7: Centerline and weight of the sample.

Number	Thickness (mm)	Centerline length (mm)	Weight (kg)
1	2.0	268.0	1.68
2	2.0	279.0	1.75
3	1.8	289.4	1.64
4	1.8	294.7	1.67

making organ is needed to compare these properties, which assess the applicability of the multifarious decision options. In this paper, a demonstration has been made by the ANN-based data-driven model to perform the optimization of the thin-wall perforated column section. Assuming that the project of the high-rise rack system requires the column which ultimate load is not less than 100000 (N), four design solutions of the thin-walled column perforated section could be empirically taken into consideration in practice, which section parameters are different in detail (Table 6). A column type will be chosen for the highest property-value ratio by the decision-making model.

The consume material of the column may be different considering the shape of different sections (Figure 18). The material calculation equation is as follows:

$$M = t * l * h * g, \quad (3)$$

where M is the material calculation equation, t is the thickness, l is the length of the center line on the cross section, h is the height (400 mm) [16], and g is the material density (7850 kg/m^3) [18].

The results in Table 7 indicate that the difference on the material consumption of four samples between the maximum and the minimum is about 6.28%. The nine parameters of the four different sections are imported into the data-driven model in turn. The results in Table 6 show that all samples meet the requirements, and number 2 has the highest ultimate loading. However, number 1 sample has high property-value ratio could be better solution because it has less reinforcement which leads to less usage of column material and lower fabrication cost in contrast with number 2 column section.

7. Conclusions

As big data techniques are increasingly used in business intelligence and industrial process, there is an urgent need to better understand and really exploit their potentialities on steel structure and civil engineering. To confront the stability challenge of high-rise AR/RS design, this paper presents a novel data-driven decision-making model on the optimization of thin-walled steel perforated sections. Taking thin-walled steel column as an example, the predictions of ultimate load from the data-driven model are made in comparison with those obtained from the FE model and physical test. It is noted that the data-driven model based on the ANN technique is very efficient, while prediction performance is much closer to the physical test than those obtained from the FE models. Of course, the advantages of FEM are determined by the thin-walled section buckling and their mechanization. However, the optimal design solutions

often need very complex decision-making process that cannot be treated adequately by only using conventional CAE tools, unless the designer possesses with full special skills, knowledge, and experience. Here, we only demonstrate that, trained with the engineering data sets from experiment and simulation, the data-driven model is able to predict the design load of different columns through self-learning, which can help the designer to make the better decision for steel member design on pallet rack. Although the results in our paper seem to be preliminary, it has been observed that the data-driven model for solving the hard problem of complicated perforated members design is very promising. With advancement in data mining and deep learning techniques, much of research activities within the civil engineering field are oriented towards making analysis-based design improvement processes more intelligent and less experience dependent, and the producer's subject intuition in industry and society will finally be replaced by smart and friendly expert systems in the future.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Authors' Contributions

Qi Lu and YiMing Song contributed the FE and predict models. Qian Xiang performed the predict system. Guanghui Yang realized the engineering application. Zhi-Jun Lyu wrote the paper.

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