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Optimal design of plane frame structures using artificial neural networks and ratio variables

Chin-Sheng Kao* and I-Cheng Yeh[a]

Department of Civil Engineering, Tamkang University, No.151, Yingzhuan-ro, Tamsui-gu, New Taipei City, Taiwan,The Republic of China

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Abstract. There have been many packages that can be employed to analyze plane frames. However, because most structural analysis packages suffer from closeness of system, it is very difficult to integrate it with an optimization package. To overcome the difficulty, we proposed a possible alternative, DAMDO, which integrate Design, Analysis, Modeling, Definition, and Optimization phases into an integrative environment. The DAMDO methodology employs neural networks to integrate structural analysis package and optimization package so as not to need directly to integrate these two packages. The key problem of the DAMDO approach is how to generate a set of reasonable random designs in the first phase. According to the characteristics of optimized plane frames, we proposed the ratio variable approach to generate them. The empirical results show that the ratio variable approach can greatly improve the accuracy of the neural networks, and the plane frame optimization problems can be solved by the DAMDO methodology.

Keywords: artificial neural networks; optimization; plane frame; ratio variable

1. 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 (Möller *et al*. 2009, Yeh 1999). One common difficulty of structural optimization design is the huge amount of structural analysis required in the optimization process. Many methodologies have been proposed to reduce the computational burden of the structural analysis. Some of them employed the design conditions as the input variables, and the optimal designs solved by other structural optimization packages as the output variables (Yeh and Chen 2012, Gholizadeh *et al*. 2012, Meon *et al*. 2012). The essential difficulty of the approach is that it must have a traditional structural optimization package to produce the optimal designs to collect the required data sets, which may be impractical in the real world.

On the other hand, some of them employed advanced hybrid techniques to solve structural optimization design with the two-phase methodology (Kodiyalam and Gurumoorthy 1997, Papadrakakis *et al*. 1998, Iranmanesh and Kaveh 1999, Perera *et al*. 2010, Lagaros *et al*. 2005,

*Corresponding author, Associate Professor , E-mail: csk@mail.tku.edu.tw
[a]Associate Professor, E-mail: 140910@mail.tku.edu.tw

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Cheng and Li 2009, Patel and Choi 2012, Gholizadeh and Salajegheh 2009, 2010a, b, Gholizadeh and Samavati 2011). In the first phase, they employed some advanced techniques, such as neural networks, fuzzy systems, and wavelet transforms, to create some predictive models of response variables of structures to be as an alternative for structural analysis package to reduce the computational burden of the structural analysis. In the second phase, they employed some advanced techniques, such as evolutionary algorithms and particle swarm optimization, to solve the optimization problem. However, they are such ad hoc approaches that they are not easy to understand.

Another common difficulty of structural optimization design is the software integration problem. Since structural analysis is the only function considered in the development of most of structural analysis software, they lack the structural optimization design function. Therefore, to solve structural optimization problems, it is necessary to combine a structural analysis software and an optimization software into an integrative system. Since most structural analysis packages suffer from closeness of system, it is very difficult to combine it with the optimization software.

To overcome these two difficulties, we proposed a possible alternative, DAMDO, which combines Design, Analysis, Modeling, Definition, and Optimization phases into an integrative environment. The key concept of DANDO is, through the Design, Analysis, and Modeling phases, to create some neural network models of response variables of structures to be as an alternative for structural analysis package (Fig. 1). Because these models are a set of regular functions, it is easy to define the users' specific optimization problems in Definition phase, and then the optimization problems can be solved with an optimization package in Optimization phase.

In this approach, since the structural analysis package is employed in the Step 2 (Analysis), and the optimization package is run in the Step 5 (Optimization), it is not necessary to directly

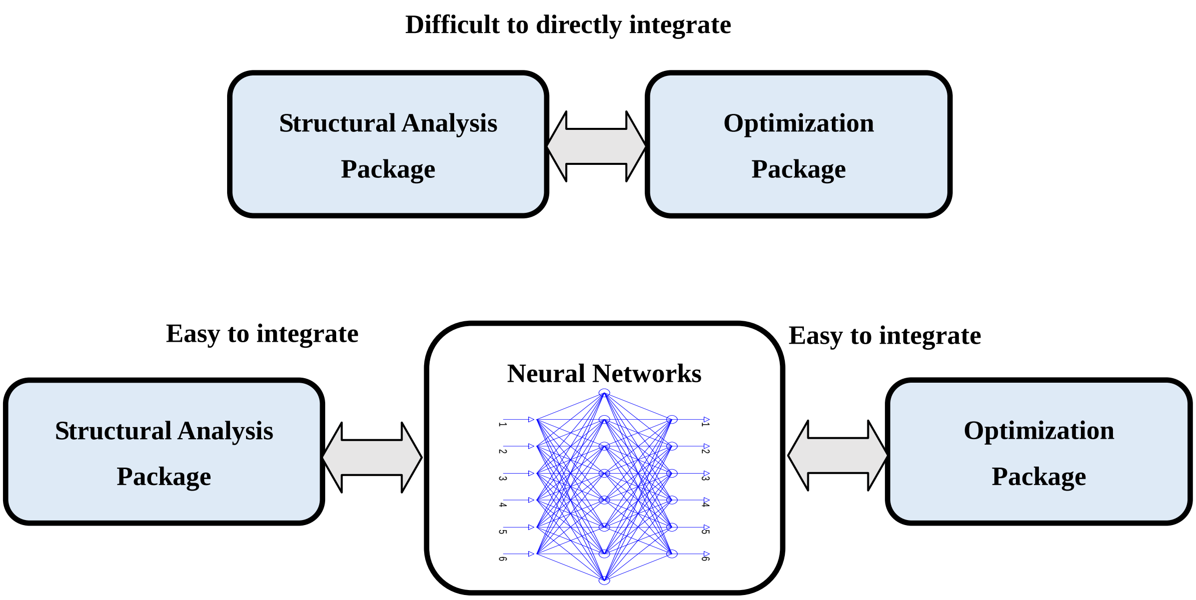

Fig. 1 Concept of direct integration and indirectly integration (DAMDO) of the structural analysis package and the optimization package

combine the structural analysis package with the optimization package into an integrative system. Therefore, this approach is promising in many engineering optimization domains which need to combine an analysis package and an optimization one to obtain the optimum solutions.

To assess the feasibility of the approach, the plane frame structure optimization design was employed. The key problem of the DAMDO approach is how to generate a set of reasonable random designs in the first phase (Design Phase). According to the characteristics of optimized plane frames, we proposed the ratio variable approach to generate a set of reasonable random designs in the first phase. In this approach, instead of directly using the width and depth of beam and column as the design variables, we used four types of ratio variables as the design variables.

The paper is set up as follows: Section 2 presents the DAMDO methodology. Section 3 presents the ratio variable approach. Then, we examined three case studies of plane frame structures to validate the methodology in Section 4. Finally, we conclude in Section 5.

2. Methodology of DAMDO

2.1 The DAMDO approach

This study proposed an alternative, DAMDO, which combine Design, Analysis, Modeling, Definition, and Optimization phases into an integrative environment as follows. Its architecture is shown in Figs. 2-4.

(1) Design: first randomly 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 width and depth of cross-section of member.

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

(3) Modeling: 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.

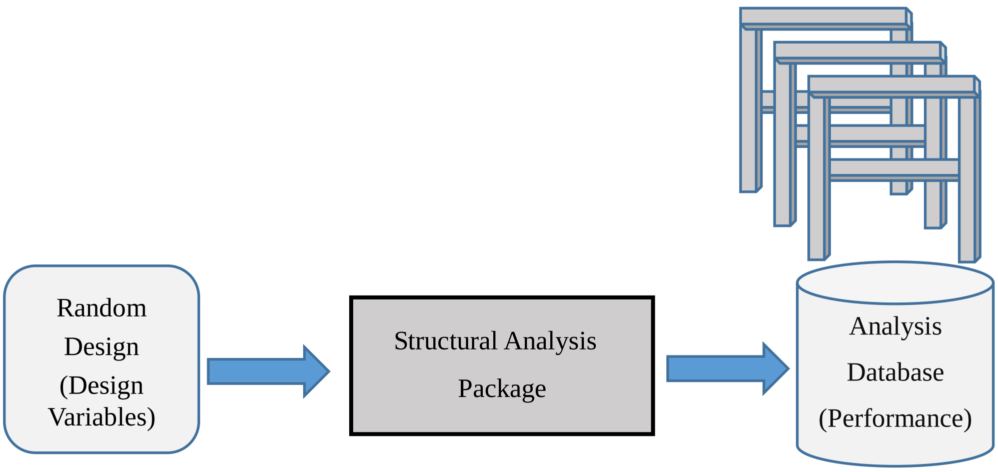

Fig. 2 Concepts of design and analysis phase

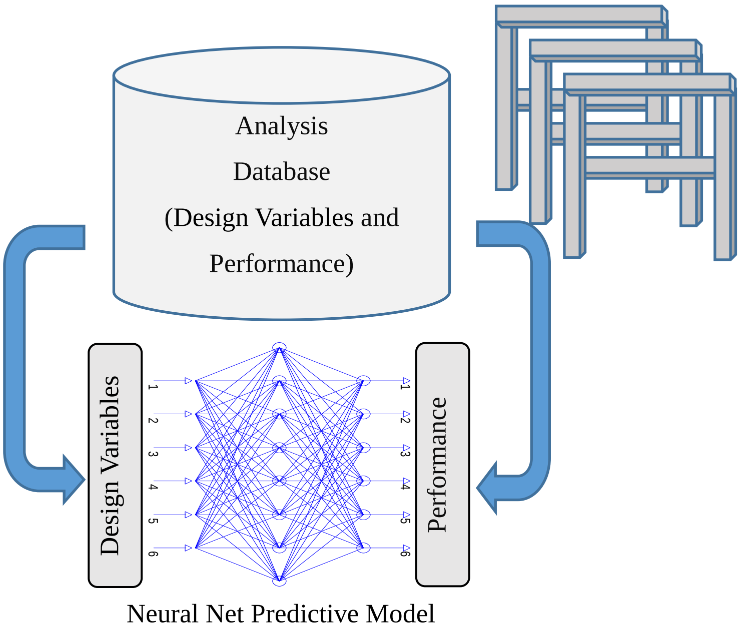

Fig. 3 Concept of modeling phase

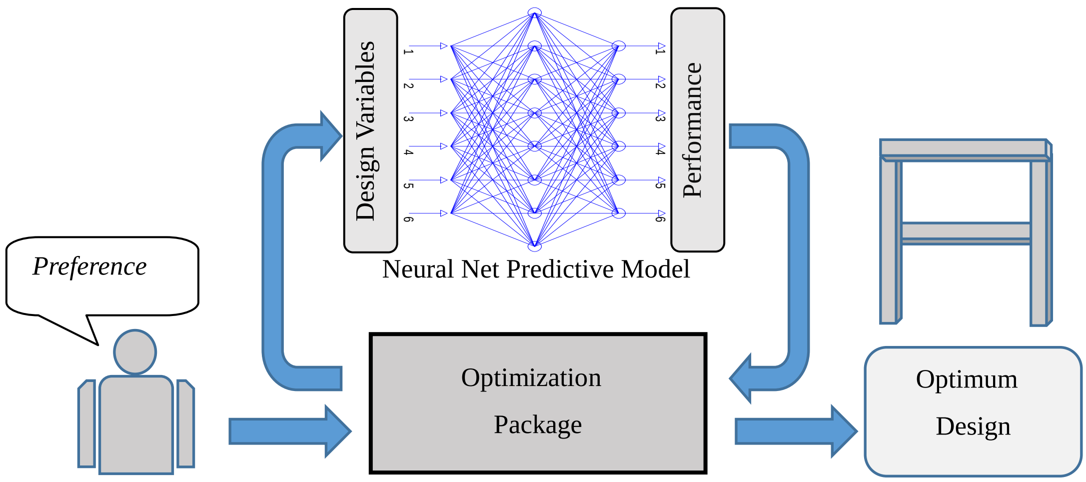

Fig. 4 Concepts of definition and optimization phase

(4) Definition: employ the design variables X and the response variables Y to define the objective function and constraint functions.

(5) Optimization: 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^*.

2.2 Artificial neural networks

The above phase 1 to 3 in section 2.1 is to create some predictive models of response variables to be as an alternative for structural analysis package. Because these models are a set of regular functions, it is easy to define the user's specific optimization problem in phase 4 with these predictive models, and then the optimization problem can be solved with optimization package in phase 5.

The reason that artificial neural network is employed instead of the traditional regression analysis in phase 3 is in structures the relations between internal forces and displacements and sizes of cross-section of members are often nonlinear. The greatest advantage of artificial neural networks is their native nonlinear system characteristic, which make them be able to build very accurate nonlinear predictive models (Haykin 2007).

The multi-layered perception (MLP) may be the most popular neural network paradigm (Haykin 2007). In this study, we employed the MLP to train the predictive systems of response variables of structures. Training means to feed the network with the training data, and to have it modify its weights, such that it can more correctly reproduce the response variables in the next iteration. The classical back-propagation general delta rule (Haykin 2007) was employed as the training rule.

In training the MLP neural networks, the following parameters were used: learning cycle = 20000 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 and momentum factor lower limit = 0.1.

2.3 The optimization and genetic algorithms

In dealing with a constrained optimization problem, DAMDO adopt the exterior penalty function method to convert the constrained optimization problem into an unconstrained optimization problem. The principle of the method is adding the penalty function into to the objective function when some constraint functions are violated. The algorithm is as follows:

(1) Convert the constrained optimization problem into an unconstrained optimization problem: Maximize the objective function

$$\varphi(\mathbf{x}) = \mathrm{F}(\mathbf{x}) - \kappa \mathrm{P}(\mathbf{x}) \tag{1}$$

Minimize the objective function:

$$\varphi(\mathbf{x}) = \mathrm{F}(\mathbf{x}) + \kappa \mathrm{P}(\mathbf{x}) \tag{2}$$

Where, κ is the penalty factor; P(x) is the penalty function

$$P(x) = \sum_{j=1}^{s} (Max(0, g_j(x)))^2 \tag{3}$$

Where, $g_j(x)$ is a constraint function.

(2) Solve the unconstrained optimization problem by unconstrained optimization techniques.

(3) Increase the penalty factor by

$$\kappa = c \cdot \kappa \tag{4}$$

Where, c is the amplification factor, and $c>1$.

(4) Repeat step (2) ~ (3) until convergence is reached.

Detailed algorithm of the exterior penalty function method can be found in the literature (Nocedal and Wright 1999).

3. Ratio variable for optimal design of frame structures

Although artificial neural networks can build rather accurate nonlinear predictive models, the smaller the dependent variable space that need predicting, the higher the predictive accuracy that can be achieved. However, the dependent variable space must involve the optimal solution. Therefore, the key problem of the DAMDO approach is how to generate a set of reasonable random designs in the first phase (Design Phase). These designs must be able to form a compact space but the space must still involve the optimal design.

In most optimized frame structures, there are some characteristics as follows.

(1) There is a reasonable range of ratio of the moment of inertia of column of the upper floor to that of the lower floor.

(2) There is a reasonable range of ratio of the moment of inertia of column to that of beam at the same floor.

(3) There is a reasonable range of ratio of the depth of column to the width of column at the same floor.

(4) There is a reasonable range of ratio of the depth of beam to the width of beam at the same floor.

According to these characteristics of optimized frame structures, we proposed a ratio variable approach to generate a set of reasonable random designs in the first phase. In this approach, instead of directly using the width and depth of beam and column as the design variables, we used the following ratios as the design variables.

(1) The ratio of the moment of inertia of column of the upper floor to that of the lower floor, I_{Ci+1}/I_{Ci}.

(2) The ratio of the moment of inertia of column to that of beam at the same floor, I_{Ci}/I_{Bi}.

(3) The ratio of the depth of beam to the width of beam at the same floor, h_i/b_i.

(4) The ratio of the depth of column to the width of column at the same floor, d_i/wi.

For example, if each floor of the three-span six-floor plane frame shown in Fig. 5 has its own design of size of beam and column, then there are 23 ratio variables as follows.

(1) The ratios of the moment of inertia of column of the upper floor to that of the lower floor, I_{C2}/I_{C1}, I_{C3}/I_{C2}, I_{C4}/I_{C3}, I_{C5}/I_{C4}, I_{C6}/I_{C5}.

(2) The ratios of the moment of inertia of column to that of beam at the same floor, I_{C1}/I_{B1}, I_{C2}/I_{B2}, I_{C3}/I_{B3}, I_{C4}/I_{B4}, I_{C5}/I_{B5}, I_{C6}/I_{B6}.

(3) The ratios of the depth of beam to the width of beam at the same floor, h_1/b_1, h_2/b_2, h_3/b_3, h_4/b_4, h_5/b_5, h_6/b_6.

(4) The ratios of the depth of column to the width of column at the same floor, d_1/w_1, d_2/w_2, d_3/w_3, d_4/w_4, d_5/w_5, d_6/w_6.

Therefore, there are 5+6+6+6=23 ratio variables. We only need one non-ratio variable, the width of the column of the first floor, w1, to present a design alternative. In other words, we can obtain all the width and depth of beam and column of each floor by these 23 ratio variables and one non-ratio variable, the width of the column of the first floor.

Through the ratio variable approach, it becomes easier to generate a set of reasonable random designs in the first phase of DAMDO.

4. Numerical examples

4.1 Method

To validate that the DAMDO approach can solve the optimization of plane frame structures, a three-span six-floor plane frame shown in Fig. 5 was examined. The static load is 3.5 ton/m, live load is 0.9 ton/m, and the seismic force of each floor is shown in Table 1. To simplify the structural analysis, the change of size of beams and columns does not affect the dead load and seismic load. The combinations of the loads are shown in Table 2. In addition, the material of the frame is assumed as a uniform material whose allowable tensile stress and compressive stress are the same.

• **Design variables**

The design variables are the ratio variables shown in Section 3 and the width of the column of the first floor. Objective function

• **Objective function**

The objective function is the total material volume of all beams and columns.

• **Constraint functions**

(1) Stress constraints

The tensile stress and compressive stress in the sections of beam and column must smaller than the allowable stress of 280kg/cm^2.

(2) Displacement constraints

The inter-story drift ratio must be smaller than 0.5%.

(3) Initial design

The initial design is shown in Table 3. The design was analyzed with the ETABS structural analysis package to obtain the internal forces of all beams and columns and the inter-story drift ratios of all floors. The results are shown in Table 4. Because the maximum stress of beam and the maximum stress of column are smaller than the allowable stress, and the maximum inter-story drift ratio is smaller than the allowable upper limit, the initial design is a feasible design.

There are three case studies in this section.

Case1: All floors have the same size design. That is, the 1~6 floors have the same size design. That is, the 1~6 floors have the same size design.

Case2: Each three floors have the same size design. That is, the 1~3 floors have the same size

Table 1 Seismic force of each floor

Floor	Seismic force (ton)
Floor 6	65.66
Floor 5	44.93
Floor 4	36.37
Floor 3	27.82
Floor 2	19.26
Floor 1	10.7

Table 2 Combinations of loads

	Dead load	Live load	Seismic force
COMBO1	1.4	0.0	0.0
COMBO2	1.2	0.5	0.0
COMBO3	1.2	0.5	1
COMBO4	1.2	0.5	-1

Table 3 Initial design of the plane frame

Floor	Beam		Column
	b (cm)	*h* (cm)	*w* (cm)
1~6 F	45	75.3	85

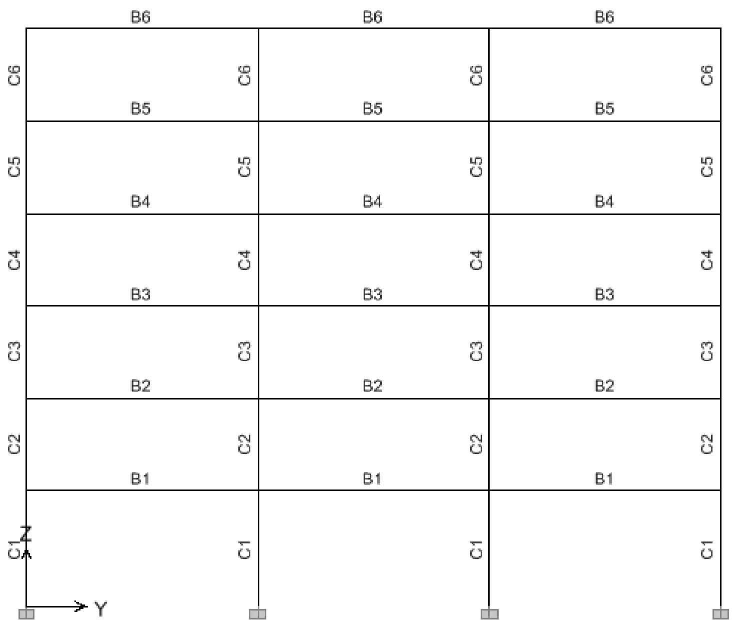

Fig. 5 Three-span six-floor plane frame

Table 4 Performance of the Initial design

Performance of the design	Value
Maximum stress in beams (kg/cm2) Y_1	280.0
Maximum stress in columns (kg/cm2) Y_2	254.6
maximum inter-story drift ratio Y_3	0.00426
Total material volume (m^3) (objective function)	119.90

design and the 4~6 floors have the same size design.

Case3: Each floor has its own size design.

Table 5 Range of design variables of the frame of Case 1

Design variables	Range
The ratio of the moment of inertia of column to that of beam, I_C/I_B	2.0~5.0
The width of the column of the first floor (cm)	50~100

4.2 Case 1: all floors have the same size design.

In this case study, all beams (or columns) of all floors have the same size. Furthermore

(1) The ratio of the moment of inertia of column of the upper floor to that of the lower floor was fixed at 1.0.

(2) The ratio between the depth of beam and the width of beam was fixed at 2.0.

(3) The ratio between the depth of column and the width of column was fixed at 1.0.

Therefore, there are only two design variables and their ranges are shown in Table 5.

The optimal design procedure used in this case study is summarized as follows.

Step 1: Design

To collect data to build predictive model, 50 designs were randomly generated in the ranges of design variables.

Step 2: Analysis

Each design was analyzed by the ETABS structural analysis package to obtain the internal force of each member and inter-story drift ratio of each floor.

Step 3: Modeling

The 50 data composed of design variables and internal force of each member and inter-story drift ratio of each floor were be employed as the training data of the artificial neural networks to build predictive models which can mimic the function of the structural analysis package. Although there are many beams and columns in a frame structure, if the maximum value of stress of beams (or columns) is smaller than the allowable stress, then all the stress constraints of beam (or column) were satisfied. Similarly, if the maximum value of the inter-story drift ratio is smaller than the allowable ratio, then all the displacement constraints were satisfied. Therefore, there are only three output variables representing the maximum value of the stress of beam (Y_1) and column (Y_2) and the maximum value of the inter-story drift ratio (Y_3) as follows.

$$Y_1 = \underset{i}{Max} \sigma_i^b \tag{5}$$

$$Y_2 = \underset{i}{Max} \sigma_i^c \tag{6}$$

$$Y_3 = \underset{i}{Max} \delta_i \tag{7}$$

Where, σ_i^b is the stress of the i-th beam; σ_i^c is the stress of the *i*-th colum; and δ_i is the inter-story drift ratio of the *i*-th floor.

To overcome the over-learning trap, cross-validation methodology was adopted. A ten-fold cross validation was employed to evaluate the performance of neural networks. That is, all the data were randomly divided into ten sets. The neural network was trained ten times, and each time a set was held out as the testing data while the remaining nine sets were used as the training data. The integrative performance of the test data of the ten time was used to assess the accuracy of network models. The root mean squared errors (RMSE) and coefficients of determination are employed to measure the accuracy of neural networks. The initial training cycles are set as 20000 cycles. After running the 20000 cycles, the optimum cycle with the minimum root mean squared error of test data can be determined. Then, the neural network would be re-trained by the optimum cycle to avoid the over-fitting trap.

If all the coefficients of determination of output variable are above 0.9, then go to the next step 4; otherwise, go to step 1 to randomly generate 50 designs to improve the accuracy of the predictive models. The reason why we employ the root mean squared error to stop the training, but we employ the coefficients of determination to stop increasing more designs to improve the accuracy of the predictive models is that there are many output units presented various response variables of structures on the output layer of the neural networks. Hence, because each response variables has its own scale, it is difficult to determine a unified threshold of RMSE to judge whether the accuracy of an output unit is adequate. While it is easy to determine a threshold of coefficients of determination, for example 0.9, to judge it.

Step 4: Definition

We can employ the design variables *X* and the response variables *Y* to define the objective function and constraint functions of the frame as follows.

$$\text{Min} \sum_{i=1}^{n} A_i L_i \tag{8}$$

Subjected to

$$Y_1 = \underset{i}{Max}\,\sigma_i^b \le 280 \tag{9}$$

$$Y_2 = \underset{i}{Max}\,\sigma_i^c \le 280 \tag{10}$$

$$Y_3 = \underset{i}{Max}\,\delta_i \le 0.005 \tag{11}$$

Where, A_i is the sectional area of ***i***-th member; L_i is the length of ***i***-th member.

Step 5: Optimization

We can 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**.

Step 6: Validation

The optimum design was analyzed by the ETABS structural analysis package to obtain the exact internal force of all members, and exact inter-story drift ratio of all floors. If all the design constraints are satisfied, then output the optimum design; otherwise, randomly generated 50 designs of frame which are close to the current optimal design, and go to step 2.

The coefficients of determination of train data and test data in the cross-validation evaluation process are in the range of 0.994~0.999 and 0.993~0.998, respectively, which validate that not only the model is accurate in train data but also in test data. The convergence histories of RMS error of train data and test data are shown in Fig. 6, and present that there are no over-learning during the 20000 learning cycles, and the convergence histories of RMS error of train data and test data almost overlap each other. Table 6 shows the optimum design obtained by the neural network. Table 7 shows the performance of the optimal design, which validate the design satisfy the stress constraints and displacement constraints.

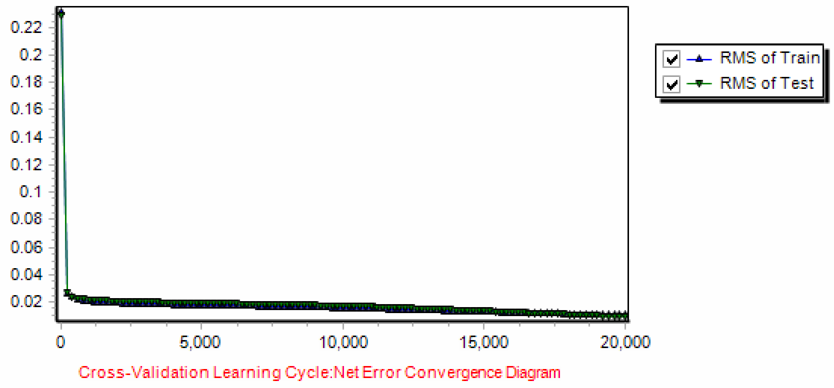

Fig. 6 The convergence histories of RMS error of train data and test data of Case 1

Table 6 Optimal design of Case 1

Floor	Beam		Column
	b (cm)	*h* (cm)	*b* (cm)
1~6 F	40.6	81.2	1~6 F

Table 7 Performance of the optimal design of Case 1

Performance of the design	Value
Maximum stress in beams (kg/cm^2) Y_1	264.6
Maximum stress in columns (kg/cm^2) Y_2	245.5
maximum inter-story drift ratio Y_3	0.00381
Total material volume (m^3) (objective function)	119.49

Table 8 Range of design variables of the frame of Case 2

Design variables	Range
The ratio of the moment of inertia of column to that of beam at 1~3 F	2.0~5.0
The ratio of the moment of inertia of column to that of beam at 4~6 F	2.0~5.0
The width of the column of the first floor (cm)	50~100

4.3 Case 2: each three floors have the same size design

In this case study, each three floors have beams and columns with the same size. Furthermore

(1) The ratios of the moment of inertia of column of the upper floor to that of the lower floor were fixed at 1.0.

(2) The ratios of the depth of beam to the width of beam were fixed at 2.0.

(3) The ratios of the depth of column to the width of column were fixed at 1.0.

Therefore, there are only three design variables and their ranges are shown in Table 8.

The optimal design procedure used in this case study is similar to that in Case 1. The coefficients of determination of train data and test data in the cross-validation evaluation process are in the range of 0.991~0.997 and 0.963~0.987, respectively, which validate that not only the model is accurate in train data but also in test data. The convergence histories of RMS error of

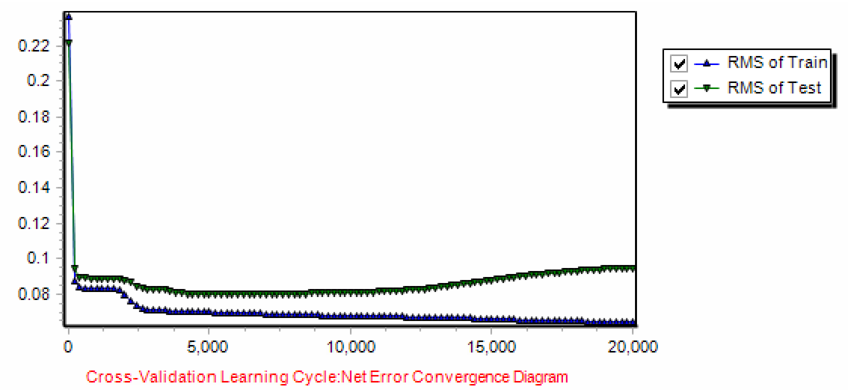

Fig. 7 The convergence histories of RMS error of train data and test data of Case 2

Table 9 Optimal design of Case 2

Floor	Beam		Column
	b (cm)	*h* (cm)	*b* (cm)
4~6 F	40.6	81.2	85
1~3 F	41	82	85

Table 10 Performance of the optimal design of Case 2

Performance of the design	Value
Maximum stress in beams (kg/cm2) Y_1	273.2
Maximum stress in columns (kg/cm2) Y_2	247.1
maximum inter-story drift ratio Y_3	0.00395
Total material volume (m^3) (objective function)	115.01

Table 11 Range of design variables of frame of Case 3

Design variables	Range
The ratios of the moment of inertia of column of the upper floor to that of the lower floor, I_{C2}/I_{C1}, I_{C3}/I_{C2}, I_{C4}/I_{C3}, I_{C5}/I_{C4}, I_{C6}/I_{C5}.	0.3~1.1
The ratios of the moment of inertia of column to that of beam at the same floor, I_{C1}/I_{B1}, I_{C2}/I_{B2}, I_{C3}/I_{B3}, I_{C4}/I_{B4}, I_{C5}/I_{B5}, I_{C6}/I_{B6}.	0.5~5.0
The ratios between the depth of beam and the width of beam, h_1/b_1, h_2/b_2, h_3/b_3, h_4/b_4, h_5/b_5, h_6/b_6	1.25~2.5
The width of the column of the first floor (cm)	50~100

train data and test data are shown in Fig. 7, and present that the over-learning happened on about 8000 learning cycles. Table 9 shows the optimum design obtained by the neural network. Table 10 shows the performance of the optimal design, which validate the design satisfy the stress constraints and displacement constraints.

4.4 Case 3: each floor has its own size design

In this case study, each floor has its own size of beams and columns. Furthermore, the ratios

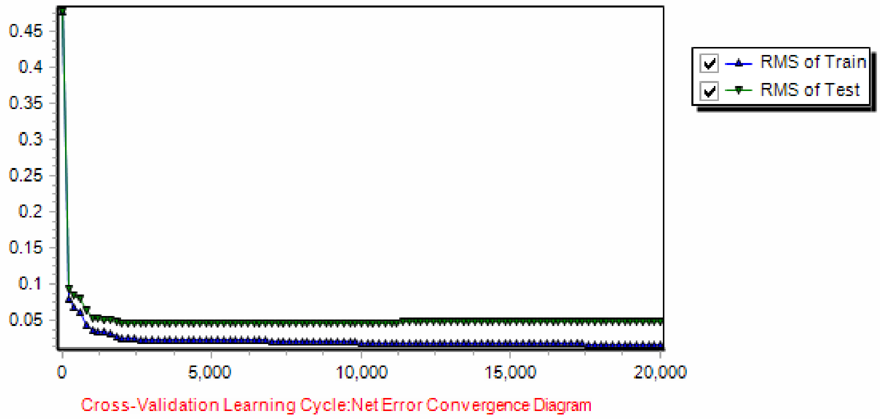

Fig. 8 The convergence histories of RMS error of train data and test data of Case 3

Table 12 Optimal design of Case 3

Floor	Ratio design variables			Beam		Column
	I_{Ci+1}/I_{Ci}	I_{Ci}/I_{Bi}	h_i/b_i	b (cm)	h (cm)	w (cm)
6F	0.48	0.96	2.00	30	60	50
5F	0.73	1.46	1.46	41	60	60
4F	0.66	0.90	1.69	45	76	65
3F	1.06	1.47	1.64	45	74	72
2F	0.39	1.10	1.78	45	80	71
1F	—	3.46	1.67	45	75	90

between the depth of column and the width of column were fixed at 1.0. Therefore, there are only 18 design variables and their ranges are shown in Table 11.

The optimal design procedure used in this case study is similar to that in Case 1. The coefficients of determination of train data and test data in the cross-validation evaluation process are in the range of 0.984~0.998 and 0.809~0.994, respectively, which validate that not only the model is accurate in train data but also in test data. The convergence histories of RMS error of train data and test data are shown in Fig. 8, and present that the over-learning happened on about 12000 learning cycles. Table 12 and Fig. 6 show the optimum design obtained by the neural network. Table 13 shows the performance of the optimal design, which validate the design satisfy the stress constraints and displacement constraints.

To validate the ratio variable approach can improve the accuracy of neural networks, we also employed the depth of beam (or column) and the width of beam (or column) as the design variables. The range of the depth and width of beam is 50~100 cm and 25~50 cm, respectively. The range of the width of column is 50~100 cm. We randomly generated 50 designs and built the neural networks. The coefficients of determination of train data in the cross-validation evaluation process are in the range of 0.8~0.9 and those of test data are in the range of 0.4~0.6, which validate that the accuracy of the predictive model is good in the train data, but rather poor in the test data. The comparisons proved that the ratio variable approach can greatly improve the accuracy of neural networks.

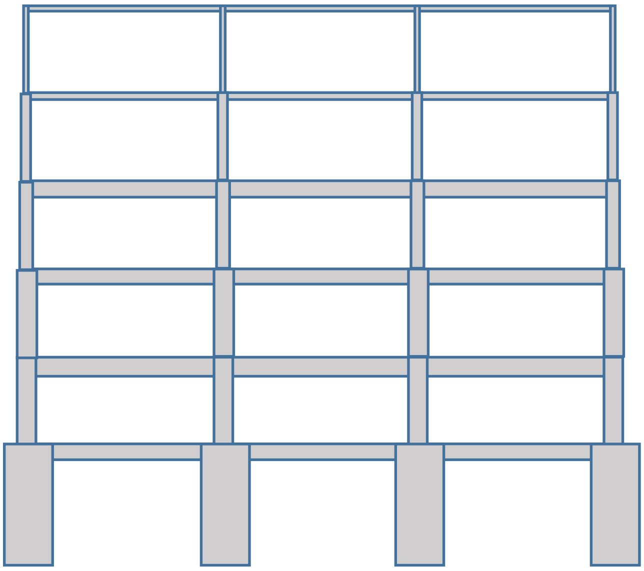

Fig. 9 Optimal design of Case 3 (the width of the column and beam in the diagram is based on the relative magnitude of the moment of inertia)

Table 13 Performance of the optimal design of Case 3

Performance of the design	Value
Maximum stress in beams (kg/cm^2) Y_1	280.0
Maximum stress in columns (kg/cm^2) Y_2	224.0
maximum inter-story drift ratio Y_3	0.00489
Total material volume (m^3) (objective function)	92.83

5. Conclusions

To solve structural optimization problems, it is necessary to combine a structural analysis package and an optimization package. Since most structural analysis packages suffer from closeness of system, it is very difficult to combine it with an optimization package. To overcome the difficulty, we proposed a feasible alternative approach, DAMDO, which combines Design, Analysis, Modeling, Definition, and Optimization phases into an integrative environment. Optimization of three cases of plane frame structures was used to validate the DAMDO approach.

According to the results of these case studies, we can conclude

1. It is feasible to replace the traditional approach, which must directly integrate a structural analysis package and an optimization package, with the DAMDO approach, which employs neural networks to integrate the two packages so as not to need directly to integrate them.

2. The ratio variable approach can greatly improve the accuracy of neural networks.

The most important advantage of the DAMDO methodology is that it is promising in many engineering optimization domains where it is very difficult to directly combine the structural analysis package with the optimization package to obtain the optimum solutions.

The most important disadvantage of the methodology is that when there are huge amount design variables in an engineering optimization application, it is still difficult to create accurate neural network models of response variables of structures to be as an alternative for structural analysis package. Fortunately, subjected to the practical considerations of construction, there are only a reasonable amount design variables in most civil engineering optimization applications. Therefore, the shortcoming may be not a serious obstacle to employ the methodology in most real applications.

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