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Optimal design of reinforced concrete plane frames using artificial neural networks

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Abstract. To solve structural optimization problems, it is necessary to integrate a structural analysis package and an optimization package. There have been many packages that can be employed to analyze reinforced concrete plane frames. However, because most structural analysis packages suffer from closeness of systems, it is very difficult to integrate them with optimization packages. To overcome the difficulty, we proposed a possible alternative, DAMDO, which integrates Design, Analysis, Modeling, Definition, and Optimization phases into an integration environment as follows. (1) Design: first generate many possible structural design alternatives. Each design alternative consists of many design variables X. (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 the models Y=f(X) to obtain the relationship functions between the design variables X and the response variables Y. (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. The RC frame optimization problem was examined to evaluate the DAMDO approach, and the empirical results showed that it can be solved by the approach.

Keywords: artificial neural networks; optimization; reinforced concrete; plane frame

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 (Yeh 1999; Iranmanesh and Kaveh 1999; Papadrakakis, *et al.* 1998; Kodiyalam and Gurumoorthy 1997; Adeli and Karim 1997). Since structural analysis is the only function considered in the development of most structural analysis packages, 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 integrated system. Although there have been many structural analysis packages, most of them suffer from closeness of systems; hence, it is very difficult to combine them with optimization packages. For example, there have been many packages that can

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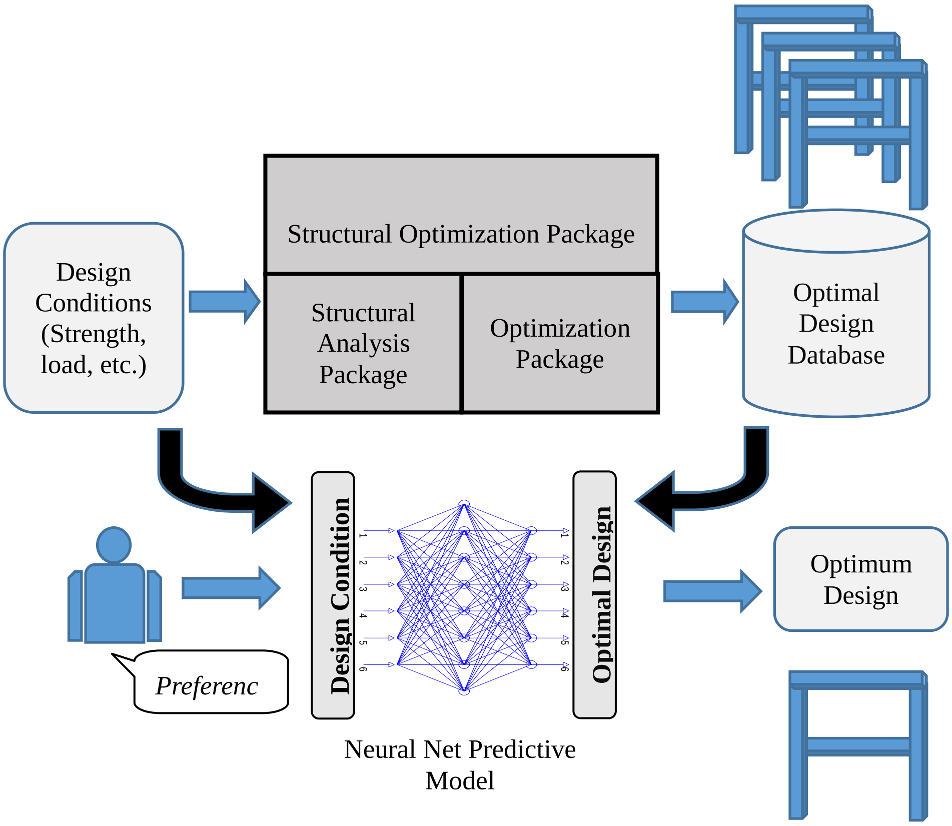

Fig. 1 The concept of the traditional approach of Structural Optimization with neural networks

be employed to analyze reinforced concrete plane frames; however, it is very difficult to combine them with optimization packages.

There has been much published literature of applications of artificial neural networks to optimize the design of structure. For example, Yeh and Chen (2009) proposed to use neural networks to predict the optimal design of reinforced concrete simple beams. The objective function is to minimize the total cost of tension reinforcement steel, stirrups and concrete. Meon *et al*. (2012) proposed to employ neural networks to predict the optimal design of frame structures. Result indicates that the neural networks can predict the optimal solution with proper training but this ability depends on the complexity of the frame structural optimization itself.

However, most of them employed the design conditions as the input variables, and the optimal designs solved by other structural optimization packages as the output variables. A lot of data was collected (input-output variable pairs) to build the optimal design database. Then, neural networks were employed to learn the knowledge implied in the database. The trained neural network becomes the optimal design system, which can predict the optimal design (output variables) according to the engineer's specific design conditions (input variables). 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. The

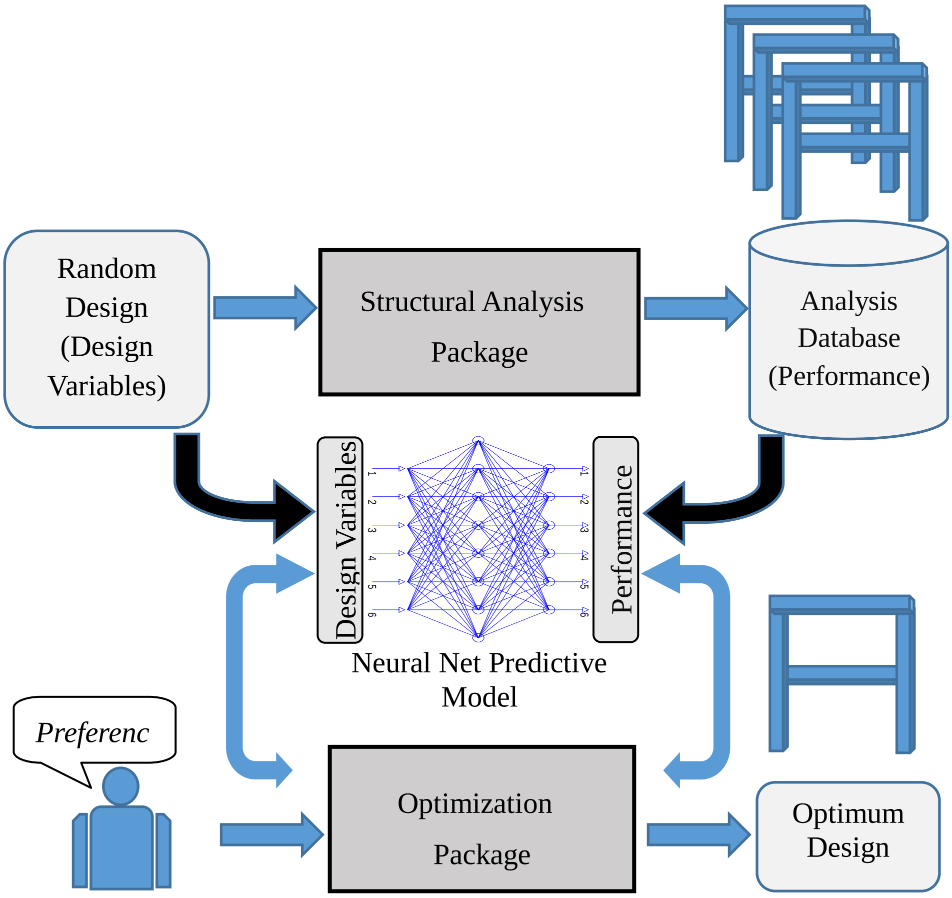

Fig. 2 The concept of DAMDO (Design, Analysis, Modeling, Definition, and Optimization)

concept of the traditional approach of structural optimization with neural networks is shown in Fig 1.

To overcome the difficulty, we proposed a possible alternative, DAMDO, which combines Design, Analysis, Modeling, Definition, and Optimization phases into an integrated environment. The key concept of DANDO is, through the Design, Analysis, and Modeling phases, to create a set of neural network models of response variables of structures to work as an alternative for the structural analysis package. Because these trained neural network models can be considered as a set of regular functions, it is easy to employ them to define the users' specific optimization problems in the Definition phase, and then the optimization problems can be solved with the optimization package in the Optimization phase.

In this approach, since the structural analysis package is employed in Step 2 (Analysis), and the optimization package is run in Step 5 (Optimization), it is not necessary to directly couple the structural analysis package with the optimization package into an integrated system.

The paper is set up as follows. Section II presents the methodology applied. We first solved the optimal designs of the RC beams and columns in Section III and IV. Then, we examined three case studies to validate the applicability of neural networks in solving the optimal designs of the RC frames in Section V. We concluded in Section VI.

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 Fig. 2.

(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.
(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 steps 1 to 3 in Section 2.1 are used to create some models of response variables to be an alternative for the structural analysis package. Because these models are a set of regular functions, it is easy to define the users' specific optimization problems in step 4, and then the optimization problems can be solved with the optimization package in step 5.

The reason that artificial neural networks is employed instead of the traditional regression analysis in step 3 is that in structures the relations between internal forces and displacements and cross-sectional areas of members are often nonlinear. The greatest advantage of artificial neural networks is their native nonlinear system characteristic, which makes them able to build very accurate nonlinear models (Zhang and Subbarayan 2002a, 2002b; Lagaros *et al*. 2005; Cheng and Li 2008; Cheng and Li 2009; Möller *et al*. 2009; Gholizadeh and Salajegheh 2010; Patel and Choi 2012). An artificial neural network is a mimic biological neural network information processing system, and has many features and advantages similar to the human brain. It uses a huge number of simple artificial neurons to mimic the ability of a biological neural network. 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 (Haykin 2007).

The classical back-propagation multilayer perceptron (MLP) (Haykin 2007) was employed. To evaluate the robustness of network architectures and parameters in building neural networks, we used the same architectures and parameters for RC beams, columns, and frames. The following network architectures were used: one hidden layer with eight processing elements using sigmoid transfer function. The following parameters were used: learning cycle = 5000 times; the range of initial weights = (-0.3, 0.3), initial learning rate = 1.0, learning rate reduction factor = 0.95, learning rate lower limit = 0.1, initial momentum factor = 0.5, momentum factor reduction factor = 0.95, and momentum factor lower limit = 0.1. We found that these network architectures and parameters are rather robust in building accurate neural networks.

2.3 The optimization and genetic algorithms

In dealing with a constrained optimization problem, DAMDO adopts 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 to the objective function when some constraint functions are violated. The algorithm is as follows (Yeh 1999):

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

Minimize the objective function:

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

Maximize the objective function:

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

where the penalty function is:

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

where, $g_j(x)$ is an inequality constraint function, $g_j(x) \le 0$; and s is the number of inequality constraint functions

(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.

Furthermore, the RC frame optimal design problem is a discrete optimization problem because the number of reinforcement steels and the increment of width and depth of RC members are discrete. To solve the discrete optimization problem, DAMDO adopts the genetic algorithms (GA) (Goldberg 1989) to solve the abovementioned unconstrained optimization problem. The greatest advantage of genetic algorithms is their native discrete optimization characteristic, which makes them able to easily solve the discrete optimization problems. Detailed algorithms can be found in the literature (Goldberg 1989).

To run the genetic algorithm, some control parameters need to be specified. To evaluate the robustness of these parameters, we used the same parameters for RC beams, columns, and frames. The control parameters in this study are as follows: population size = 100; crossover rate = 60%; mutation rate = 0.5%; initial penalty factor =1.0; amplification factor=1.1; evolution generation =

100. We found that these parameters are rather robust for the optimization of RC members and frames.

3. RC beam design

3.1 Method

- **Design variables**

The design variables of the RC beam include width of beam (X_1), effective depth of beam (X_2), number of tension reinforcement steels (X_3), size of tension reinforcement steel (X_4), number of compression reinforcement steels (X_5), size of compression reinforcement steel (X_6), yield strength of reinforcement steel (X_7), and compressive strength of concrete (X_8). A typical RC beam is shown in Fig. 3.

- **Objective function**

The objective function is the total cost of the reinforcement steel and concrete.

$$Cost = C_c \times b \times h + C_r \times (A_s + A_s') \tag{5}$$

Where C_c = unit price of concrete; C_r= unit price of reinforcement steel; b=width of beam; h=depth of beam; A_s=total area of tension reinforcement steel; A_s'= total area of compression reinforcement steel.

- **Constraint functions**

There are three types of inequality constraints formulated according to the requirements presented in the design code.

(1) Minimum resisting moment

The strength requirement for flexure takes the inequality form of

$$\phi \cdot M_n \geq M_u \tag{6}$$

where, ϕ =0.9 is the strength reduction factor for flexure; M_n is the nominal resisting moment; M_u is the factored bending moment. Although the strength reduction factor in the current ACI code is a function of the strain in the extreme tensile reinforcement, which varies from 0.65 to 0.9, the RC design code in Taiwan (Civil 401-86a) fixes the factor to 0.9 for RC beam members.

(2) Maximum reinforcement steel ratio

The RC design code in Taiwan (Civil 401-86a) limits the amount of tension steel to not be more than 75% of that required for a balanced section, that is,

$$\rho \le \rho_{\max} \tag{7}$$

where

$$\rho = \frac{A_s}{bd} \tag{8}$$

$$\rho_{max} = 0.75\rho_b + \rho' \left(f_s' / f_y \right) \tag{9}$$

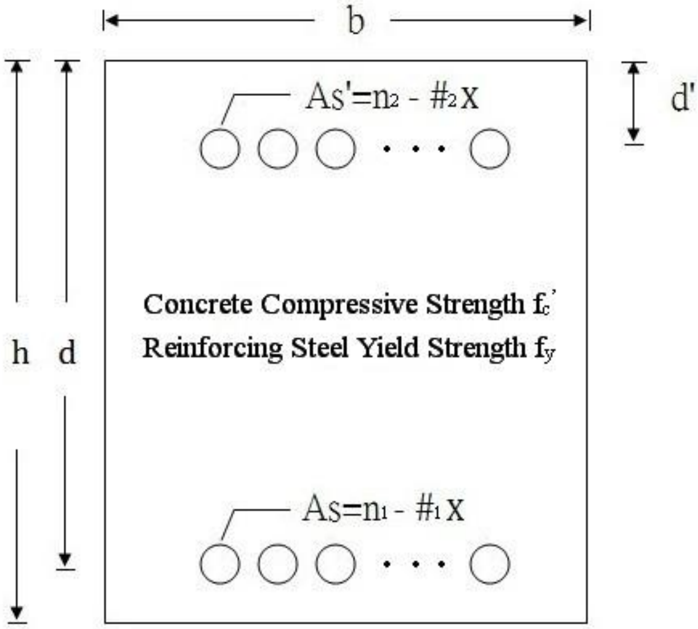

Fig. 3 RC beam

Table 1 Minimum width of beam (cm)

# of reinforcement size of reinforcement	2	3	4	5	6	7	8	9	10
#5	15	20	24	28	32	37	41	44	49
#6	17	20	25	29	34	38	43	47	51
#7	17	22	27	30	36	41	46	51	56
#8	18	23	28	33	38	43	48	53	58
#9	19	24	30	36	42	47	53	58	64
#10	20	27	33	39	46	52	58	65	71
#11	20	28	36	42	50	57	64	71	79

Table 2 The range of design variables of RC beam

design variables	range
width of beam (cm) (X_1)	15~78
effective depth of beam (cm) (X_2)	20~83.5
number of tension reinforcement steels (X_3)	2~9
size of tension reinforcement steel (X_4)	#5~#11
number of compression reinforcement steels (X_5)	2~9
size of compression reinforcement steel (X_6)	#5~#11
yield strength of the reinforcement f_y (ton/cm^2) (X_7)	2.8, 3.5, 4.2, 5.6
compressive strength of concrete $f_{c'}$ (kg/cm^2) (X_8)	140, 175, 210, 280, 350, 420

Table 3 The optimal design of RC beam

Design variables or functions	This study		Literature (Yin, 2009)
	Sol. 1	Sol. 2	
width of beam (cm) (X_1)	36	35	28
effective depth of beam (cm) (X_2)	52	50	72.5
number of tension reinforcement steels (X_3)	4	4	3
size of tension reinforcement steel (X_4)	11	11	11
number of compression reinforcement steels (X_5)	2	2	4
size of compression reinforcement steel (X_6)	7	9	8
yield strength of reinforcement steel (ton/cm^2) (X_7)	5.6	5.6	5.6
compressive strength of concrete (kg/cm^2) (X_8)	420	420	350
Exact resisting moment $\phi \cdot M_n$	100.3	100.3	98.71
Objective function (NT dollar/meter of beam)	451	427	487

(3) Minimum width of beam

To ensure the effect of the bond between the reinforcement steel and concrete, there must be adequate spacing between reinforcement steels. Therefore, the greater the reinforcement steel number and size, the greater the required width of beam.

$$b \geq b_{\min} \tag{10}$$

where $b_{\min}$ = required minimum width of beam shown in Table 1.

3.2 Case study

The RC beam in the literature (Yin 2009) is used as a test problem. Based on the often-used materials and customs in Taiwan, this paper selects four kinds of yield strength of the tension reinforcement steel: 2.8, 3.5, 4.2, 5.6 ton/cm^2, and six kinds of compressive strength of the concrete: 140, 175, 210, 280, 350, 420 kg/cm^2. The ranges of design variables of the RC beam are listed in Table 2. The factored bending moment is 100 m-ton. The ratio of price per m^3 of

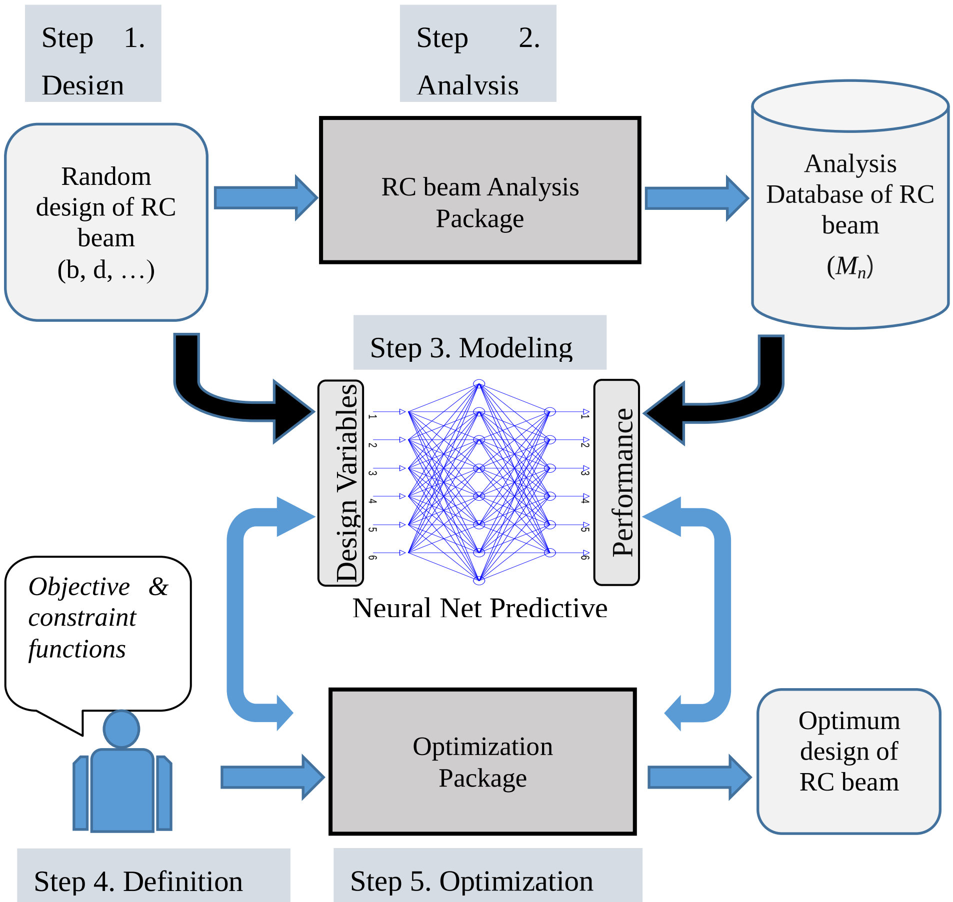

Fig. 4 The concept of DAMDO for RC beam

reinforcement steel to concrete is taken as 8 to 1. The price of concrete is 2000 NT dollars per cubic meter.

The optimum design procedure used in this case study is shown in Fig. 4 and 5 and summarized as follows.

- **Step 1. Design**

To collect data to build a predictive model, 100 designs of the RC beam were randomly generated in the ranges of design variables.

- **Step 2. Analysis**

The 100 designs were analyzed by a RC beam analysis program to obtain their nominal resisting moment.

- **Step 3. Modeling**

The 100 data composed of design variables and nominal resisting moment were employed as the training data of the artificial neural network to build the model which can mimic the function of the RC beam analysis program; that is, the inputs X of the model are the width of beam (X_1), effective depth of beam (X_2), number of tension reinforcement steels (X_3), size of tension reinforcement steel (X_4), number of compression reinforcement steels (X_5), size of compression reinforcement steel (X_6), yield strength of reinforcement steel (X_7), and compressive strength of concrete (X_8); and the output Y of the model is the nominal resisting moment. To overcome the

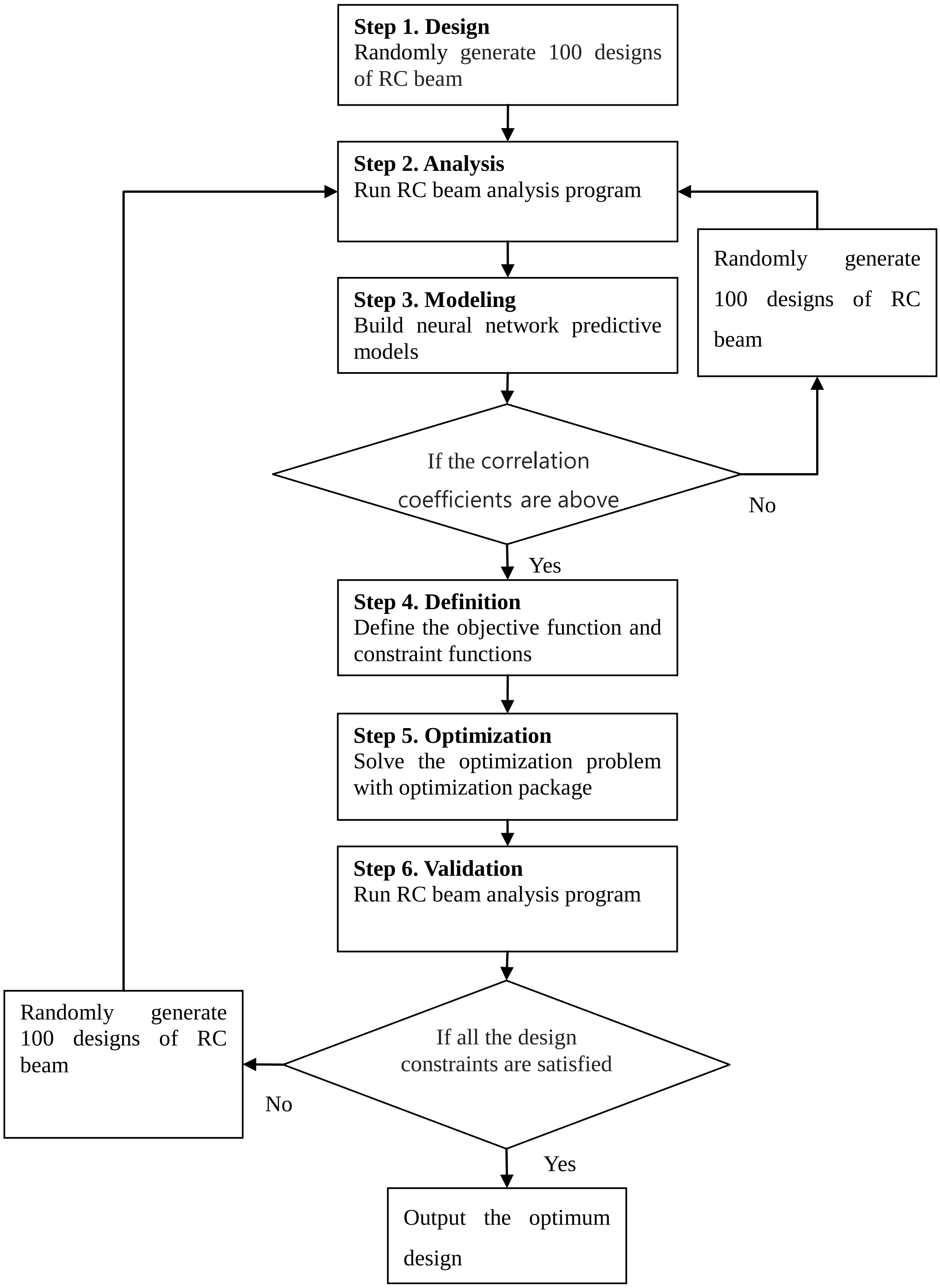

Fig. 5 The flowchart of DAMDO for RC beam

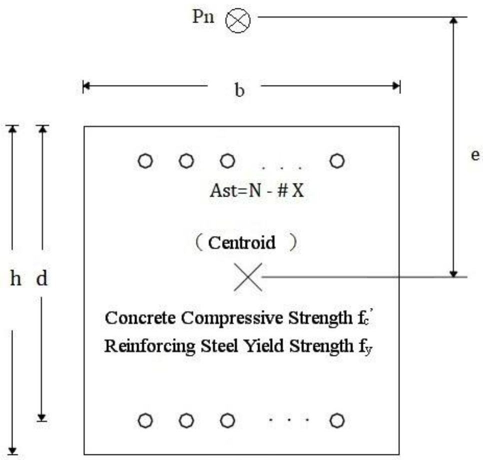

Fig. 6 RC column

over-learning trap, cross-validation methodology was adopted. If the correlation coefficients are above 0.9, then go to the next step 4; otherwise, randomly generate 100 designs of RC beam, and go to step 2.

- **Step 4. Definition**

The design variables X and the response variables Y were employed to define the objective function and constraint functions of the RC beam according to the Equation (5)~ Equation (10).

- **Step 5. Optimization**

The optimization software was used to solve the optimization problem consisting of the objective function and constraint functions to produce the optimum design variables X*.

- **Step 6. Validation**

The optimum design was analyzed by a RC beam analysis program to obtain their exact nominal resisting moment. If all the design constraints are satisfied, then output the optimum design; otherwise, randomly generate 100 designs of RC beam which are close to the current optimal design, and go to step 2.

Because the genetic algorithms can generate many optimized solutions, Table 3 shows the best two solutions of the RC beam design problem. The results show that the two optimum designs obtained by the neural network are better than those in the literature (Yin 2009), which proves that the DAMDO approach is feasible and excellent.

4. RC column design

4.1 Method

Traditionally the RC columns can be designed by looking up the interactive diagram of axial force and bending moment, but the process cannot obtain the optimum design. This section will explore the feasibility of using the DAMDO approach to obtain the optimal design of the RC column.

- **Design variables**

The design variables of the RC column include width of column (X_1), depth of column (X_2), number of reinforcement steels (X_3), size of reinforcement steel (X_4), yield strength of reinforcement steel (X_5), and compressive strength of concrete (X_6). A typical RC column is shown in Fig. 6.

- **Objective function**

The objective function is the total cost of the reinforcement steel and concrete.

$$Cost = C_c \times b \times h + C_r \times A_s \tag{11}$$

where, C_c = unit price of concrete; C_r= unit price of reinforcement steel; b=width of column; h=depth of column; A_s=total area of reinforcement steel.

- **Constraint functions**

There are four types of inequality constraints formulated according to the requirements presented in the RC design code in Taiwan (Civil 401-86a)

Minimum resisting moment

The strength requirement for the bending moment takes the inequality form of

$$\phi \cdot M_n \geq M_u \tag{12}$$

where, ϕ =0.65 is the strength reduction factor for the column; M_n is the nominal resisting moment; M_u is the factored bending moment.

Table 4 The range of design variables of RC column

design variables	range
width of column (cm) (X_1)	15~78
effective depth of column (cm) (X_2)	20~83.5
number of reinforcement steels (X_3)	2~9
size of reinforcement steel (X_4)	#5~#11
yield strength of the reinforcement f_y (ton/cm^2) (X_5)	2.8, 3.5, 4.2, 5.6
compressive strength of concrete $f_{c'}$ (kg/cm^2) (X_6)	140, 175, 210, 280, 350, 420

Table 5 The optimal design of RC column

Design variables or functions	This Study	Literature (Song 1996)
width of beam (cm) (X_1)	23	27
effective depth of beam (cm) (X_2)	74	73
number of reinforcement steels (X_3)	6	6
size of reinforcement steel (X_4)	#10	#9
yield strength of reinforcement (ton/cm^2) (X_5)	5.6	5.6
compressive strength of concrete (kg/cm^2) (X_6)	420	420
Real resisting moment $\phi \cdot M_n$	80.0	80.0
Real resisting axial force $\phi \cdot P_n$	110.8	101
Objective function (NT dollar/meter of column)	499	518

(1) Minimum resisting axial force

The strength requirement for axial force takes the inequality form of

when $$P_u \geq \phi \cdot P_b : \ \phi \cdot P_n \geq P_u \tag{13}$$

when $$P_u \leq \phi \cdot P_b : \ \phi \cdot P_n \leq P_u \tag{14}$$

where, ϕ =0.65 is the strength reduction factor for the column; P_n is the nominal resisting axial force; P_u is the factored axial force; P_b is the balanced axial force. Although the strength reduction factor in the current ACI code is a function of the strain in the extreme tensile reinforcement, which varies from 0.65 to 0.9, the RC design code in Taiwan (Civil 401-86a) fixes the factor to 0.65 for RC column members.

(2) Minimum width of column

To ensure the effect of the bond between the reinforcement steel and concrete, there must be adequate spacing between reinforcement steels. Table 1 shows the required minimum width of the column.

(3) Limits of reinforcement steel ratio

The design code limits the reinforcement steel ratio of column to 1%~8%.

$$0.01 \leq \frac{A_s}{bh} \leq 0.08 \tag{15}$$

4.2 Case study

The RC column in the literature (Song 1996) is used as a test problem. The ranges of design variables of the RC column are listed in Table 4. The factored bending moment is 80 m-ton, and the factored axial force is 100 ton. The ratio of price per m3 of reinforcement steel to concrete is taken as 8 to 1. The price of concrete is 2000 NT dollars per cubic meter.

The optimum design procedure used in this case study is similar to that used in the RC beam case study. Table 5 shows the results. The optimum design obtained by the neural network is better than those in the literature (Song 1996), which proved that the DAMDO approach is feasible and excellent.

5. RC frame design

5.1 Method

- **Design variables**

The design variables of the RC beam include width of beam, depth of beam, number of tension reinforcement steels, size of tension reinforcement steel, number of compression reinforcement steels, and size of compression reinforcement steel. The design variables of the RC square-type column include width of column, number of reinforcement steels, and size of reinforcement steel.

- **Objective function**

The objective function is the total cost of the reinforcement steel and concrete of all the beams and columns.

- **Constraint functions**

The constraint functions of beams and columns are the same as those in Section 3 and 4. Moreover, the depth of the beam must be smaller than double the width of the beam, and the depth of the column must be the same as the width of the column.

There are three case studies in this section.

Case 1. All floor one size design with 5 cm size Increment

Case 2. One floor one size design with 5 cm size Increment

Case 3. One floor one size

Table 6 The 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 7 The range of design variables of RC frame

design variables	range
width of beam (cm) (X_1)	15~60
effective depth of beam (cm) (X_2)	20~83.5
number of tension reinforcement steels (X_3)	2~9
size of tension reinforcement steel (X_4)	#5~#11
number of compression reinforcement steels (X_5)	2~9
size of compression reinforcement steel (X_6)	#5~#11
width (depth) of column (cm) (X_7)	20~120
number of reinforcement steel of column (X_8)	2~30
size of reinforcement steel of column (X_9)	#5~#11

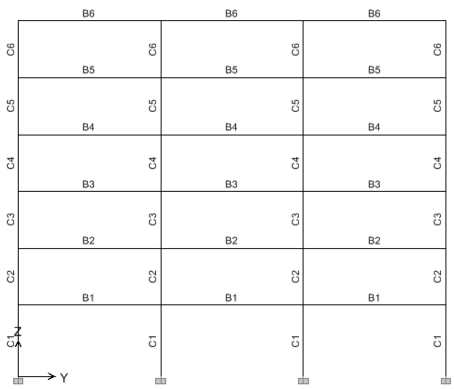

Fig. 7 RC plane frame

5.2 Case 1. All floor one size design with 5 cm size Increment

In this case study, all members of all floors have the same size. Therefore, there are 6 design variables for the beam and 3 design variables for the column, 9 design variables in total. The ranges of design variables are shown in Table 7. The size increment is 5 cm for the width and depth of beams and columns.

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

- **Step 1. Design**

To collect data to build a predictive model, 100 designs of RC plane frame were randomly generated in the ranges of design variables.

- **Step 2. Analysis**

Each RC plane frame was analyzed by the ETABS structural analysis package to obtain the internal force of all members. And all the RC beams and columns in each design were analyzed by a RC beam and column analysis program to obtain their nominal resisting moment and axial force.

- **Step 3. Modeling**

The 100 data composed of design variables, internal force, and nominal resisting moment and axial force were employed as the training data of the artificial neural networks to build the models which can mimic the functions of the RC beam, column, and frame analysis package; that is, the inputs X of the model are width of beam, depth of beam, etc. The outputs Y of the model are the internal bending moment of each beam, the internal bending moment and axial force of each column, nominal resisting moment of each beam, and nominal resisting moment and axial force of each column. To overcome the over-learning trap, cross-validation methodology was adopted. If the correlation coefficients are above 0.9, then go to the next step 4; otherwise, randomly generate 100 designs of RC frame, and go to step 2.

- **Step 4. Definition**

The design variables X and the response variables Y can be employed to define the objective function and constraint functions of the RC frame according to the design conditions presented in Ssection 5.1.

- **Step 5. Optimization**

The optimization software can be used to solve the optimization problem consisting of the objective function and 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 all the RC beams and columns were analyzed by the RC beam and column analysis program to obtain their exact nominal resisting moment and/or axial force. If all the design constraints are satisfied, then output the optimum design; otherwise, randomly generate 100 designs of RC frame which are close to the current optimal design, and go to step 2.

Table 8 shows the optimum design obtained by the neural network. We also used the perturbation approach, which check all the designs close to the above optimum design, to find the alternative optimum design as shown in the last column of Table 8. The optimum design obtained by the neural network is better than the one obtained by the perturbation approach, which proves that the DAMDO approach is excellent.

Table 8 The optimal design of RC frame of Case 1

Design variables or functions		This study	perturbation approach
Design variables of beam	width of beam (cm) (X_1)	40	40
	effective depth of beam (cm) (X_2)	75	80
	number of tension reinforcement steels (X_3)	4	4
	size of tension reinforcement steel (X_4)	11	11
	number of compression reinforcement steels (X_5)	2	2
	size of compression reinforcement steel (X_6)	6	5
Design variables of column	width of column (cm) (X_7)	100	95
	number of tension reinforcement steels (X_8)	18	16
	size of tension reinforcement steel (X_9)	10	11
Objective function (NT dollar)		825926	846519

Table 9 The optimal design of RC frame of Case 2

Design variables or functions		Floor					
		1	2	3	4	5	6
Design variables of beam	width	35	40	35	35	35	30
	effective depth	65	75	70	70	70	60
	number of tension rein.	3	4	4	4	4	3
	size of tension rein.	11	11	11	11	11	11
	number of compression rein.	2	2	3	2	2	2
	size of compression rein.	7	9	6	7	5	5
Design variables of column	width	100	95	90	85	75	50
	number of tension rein.	16	14	10	12	6	6
	size of tension rein.	11	9	10	9	11	10
Objective function (NT dollar)		573193					

Table 10 The optimal design of RC frame of Case 3

Design variables or functions		Floor					
		1	2	3	4	5	6
Design variables of beam	width	30	38	37	36	35	29
	effective depth	60	76	74	72	70	58
	number of tension rein.	3	4	4	4	3	3
	size of tension rein.	11	11	11	11	11	11
	number of compression rein.	2	3	4	2	3	2
	size of compression rein.	6	8	6	7	7	5
Design variables of column	width	95	92	88	81	63	47
	number of tension rein.	18	14	8	12	6	6
	size of tension rein.	11	9	11	9	10	11
Objective function (NT dollar)		561630					

5.3 Case 2. One floor one size design with 5 cm size Increment

In this case study, each floor has one size for beams and for columns. Therefore, there are 6 design variables for the beams of each floor and 3 design variables for the columns of each floor. Because there are 6 floors, we have (6+3)*6=54 design variables in total. The ranges of design variables are the same as those in Case 1. The size increment is 5 cm for the width and depth of beams and columns.

Table 9 shows the optimum design obtained by the neural network. The cost of the optimal design of case 2 is 30.6% cheaper than that of case 1, which points out that using various designs for each floor can significantly reduce the cost.

5.4 Case 3. One floor one size design with 1 cm size Increment

In this case study, each floor has one size for beams and for columns. The size increment is 1 cm for the width and depth of beams and columns.

Table 10 shows the optimum design obtained by the neural network. The cost of the optimal design of case 3 is 32.0% cheaper than that of case 1. However, comparing the results with those in Case 2 which reduces size increment to 1 cm for the width and depth of beams and columns cannot significantly reduce more cost.

6. 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 systems, it is very difficult to combine them 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 integrated environment. The RC beam, column, and plane frame optimization problem were examined to evaluation the DAMDO approach. According to the results, the following conclusions can be obtained:

1. The optimal designs of the RC beam, the RC column, and the RC frame obtained by the DAMDO approach was better than the optimal designs in some literature, which showed this approach is an effective methodology to solve the optimization problem of RC members and frames.
2. The DAMDO approach can employ neural networks to indirectly integrate the structural analysis package and the optimization package. Therefore, this approach 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.

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