Artificial neural network model for optimum design of tubular columns

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Abstract: - In structural engineering problems, an optimum design is also a must like safety and comfort. Most of the structural optimization problems are non-linear and cannot be mathematically solved. For that reason, iterative methods like the use of a metaheuristic algorithm are generally used. The optimization process may last too long. In the present study, a prediction system based on artificial neural networks (ANNs) was developed for the cost optimization of tubular column by learning with optimum result found according to flower pollination algorithm. According to the result, the ANNs model is effective to find close solutions to optimum values obtained by the employed optimization method.

Key-Words: Artificial neural network, metaheuristic algorithms, flower pollination algorithm, tubular column, prediction.

1 Introduction

In design of structures, besides safety and esthetic, providing of economical design with cost optimization, is an important engineering problem. For this reason, determining sizes of structural members right is design engineer's duty and most time engineer's experience plays an important role in this problem. The aim is to find the best sizes in the minimum possible duration for structural members by ensuring necessary conditions, so optimization techniques are used in this situation.

However, optimization process last long times in designs which have lots of members and this situation makes it hard to realize necessary alterations and improvements and cause to not predict of costs in right time, too. For that reason, using of artificial intelligence and machine learning techniques with metaheuristic algorithms may be

useful. One of these techniques is multilayer artificial neural networks (ANN), which is frequently preferred in different engineering problems. Senyiğit et. al. [1] used artificial neural networks, that is trained with heuristic methods which are genetic (GA) and bee algorithms to determine of optimal lot sizes that can ensure minimum of total cost under demand and price uncertainness. Song et. al. [2] used ANN and GA for optimal temperature and airflow distribution to provide control of energy using. On the other hand, Kant ve Sangwan [3] combined GA and ANN, to determine values of optimal machining parameters that provide to occur surface roughness minimum. In addition, real application was realized for machining with the aim of evaluating performance of ANN-GA model in this study. Hafezi et. al. [4] developed an agent system that designed with bat algorithm (BA) and ANN, which can predict DAX stock prices by using quarterly cycles of eight years.
In civil engineering, some studies have been developed for predicting of optimum values of problem parameters that are intended for the aim of designed model, rapidly. For example; Bowden et. al. [5] developed a model that can determine by predicting from 14 days previous salinity amount in Murray River in South Australia with ANN and GA. To predict unconfined compressive strength of granite and limestone rock samples from Malaysia's area, ANNs with particle swarm optimization (PSO) method which will provide increase of network performance, were used by Momeni et. al.[6]. Hoang and Pham [7] combined firefly algorithm (FFA) and ANNs to evaluate the slope stability.
One of these studies related with structural engineering is to estimate the tender price amounts for bridge construction projects by using ANN and GA by Chou et al. [8]. Gholizadeh [9] realized a model for performance-based optimal seismic design of three, six and twelve-story planar steel moment frames employing firefly algorithm (FFA) and ANNs. Mashhadban et. al. [10] predicted self compacting concrete properties by using fiber mixture and pure concretes. Chatterjee et. al. [11] determined structural failure of multistory reinforced concrete buildings employing ANN and PSO.
In this study, optimum central diameter and the thickness are determined to provide minimum cost for a tubular column under compressive load. Optimization process was performed using flower pollination algorithm (FPA) and a prediction system based on artificial neural networks was developed by using the obtained optimal design values.

2 The optimization problem

In the present study, the cost optimization of tubular column under compressive load is investigated. The model of the tubular column including a section A-A is given in Fig. 1 [12]. The column is excited by an axial force (P) and the length of the tubular column is *l*. P and *l* together with yield stress (σ_y), density (ρ) and modulus of elasticity (E). The central diameter (d) and the thickness of the tubular column (t) are design variables to minimize. Outer (d_0) and inner (d_i) diameter are related to the design variables as defined below.

$$d_i = d - \frac{t}{2} \tag{1}$$

$$d_0 = d + \frac{t}{2} \tag{2}$$

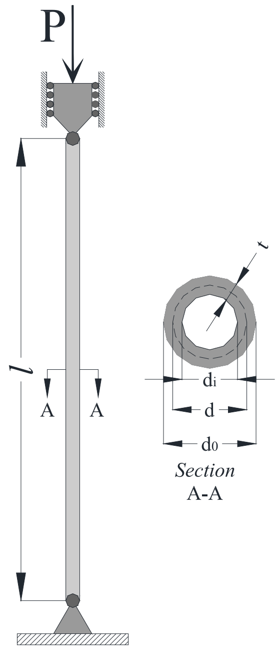

Figure 1. Tubular column and A-A cross-section

The objective function of the optimization can be written as follows:

$$f(d,t) = 9.8dt + 2d \tag{3}$$

The problem has six design constraints. Two of them are related to design and the other are related to minimum and maximum ranges. The first constraint (g_1) is considered for compressive capacity of column. It is formulated as follows:

$$g_1 = \frac{P}{\pi dt\,\sigma_y} - 1 \le 0 \tag{4}$$

The second constraint (g_2) is related with the buckling force capacity and it is written as Eq. (5).

$$g_2 = \frac{8PL^2}{\pi^3 Edt\,(d^2+t^2)} - 1 \leq 0 \quad (5)$$

The minimum and maximum ranges of d are 2 cm and 14 cm, respectively. For that case, third and fourth constrains are formalized as Eq. (6) and (7), respectively.

$$g_3 = \frac{2.0}{d} - 1 \leq 0 \quad (6)$$

$$g_4 = \frac{d}{14} - 1 \leq 0 \quad (7)$$

The minimum and maximum ranges of t are 0.2 cm and 0.9 cm and the last constrains are written as follows:

$$g_5 = \frac{0.2}{t} - 1 \leq 0 \quad (8)$$

$$g_6 = \frac{t}{0.9} - 1 \leq 0 \quad (9)$$

3 Flower pollination algorithm

In the present study, machine learning is done according to optimum results for different P and *l* values. The optimum design variable values were obtained by using flower pollination algorithm developed by Yang [13-14].

Flowering plants reproduce via pollination in nature. The pollination process can be done by pollinators such as insects, birds, bats, other animals and wind or self-pollination like self-fertilization of flowers. Pollinators obey the rules of Lévy flight and global pollination is formalized with a Lévy distribution (L) as given in Eq. (10)

$$x_i^{t+1} = x_i^t + L(x_i^t - g_*) \quad (10)$$

In this formulation, x_i^{t+1} is the updated new solution of design variable and x_i^t is the existing solution. g* is the best current solution. *i* represents population and *t* is the iteration number.

Self-pollination is formalized with linear random distribution (ε) between 0 and 1 as seen in Eq. (11).

$$x_i^{t+1} = x_i^t + \varepsilon(x_j^t - x_k^t) \quad (11)$$

In the local optimization, existing j^{th} and k^{th} solution of population (x_j^t and x_k^t) are used. In iterative optimization, the two optimization types are used with a switch probability (p).

4 Artificial Neural Networks

Artificial Neural Networks (ANNs) is an efficient tool used in estimation processes. The ANN structure and the training algorithm used for the application are important parameters for obtaining the optimum results. Hence, specifying these parameters for the subject of interest is a significant step in designing an ANN model.

In this study, feed-forward networks and back-propagation training algorithm are used for the application. This ANN architecture has a three-layered structure. The input and output layers represent independent variables and dependent variables of the system, respectively, while the hidden layer is used to perform the transformations [15].

5 Numerical examples

In the first stage of numerical applications, 10000 P-L couples were generated by randomly choosing axial force (P) in between 100-5000 kgf and the column length (L) in between 100-800 cm. Optimum values of center diameter (d) and thickness (t) of column were generated within minimum and maximum values of design parameters and then constraints and objective function values were determined with optimization algorithm.

In the second stage, optimum values were trained by ANN. This ANN structure has two input nodes and three output nodes. For each node, input values are P and L while output values are d, t, and minimum objective function values. The number of hidden neurons is chosen to be 10. Then, the outputs were predicted by realizing a decision process for new samples (random P-L couples) with ANN. In Table 1, the optimization results and in Tables 2-4, prediction results of d, t and min f(d,t) are shown including error metric values of mean absolute error (MAE), mean absolute percent error (MAPE) and mean-squared error (MSE).

The design constraint values (g1 and g2) were analyzed by calculating with predicted values to show the success of prediction process. Results are shown in Table 5. Only one of the constraints is violated.

TABLE I. OPTIMIZATION RESULTS OF NEW SAMPLES

P (kgf)	*L (cm)*	d (cm)	t(cm)	g_1	g_2	Min f(d,t)
171	551	4,2840	0,200	-0,8729	0	16,9646
1373	306	5,7978	0,200	-0,2462	-1,11x10^{-16}	22,9593
958	110	2,3883	0,255	-1,11x10^{-16}	-1,11x10^{-16}	10,7535
749	411	5,7669	0,200	-0,5866	-2,22x10^{-16}	22,8371
2043	701	11,5059	0,200	-0,4348	0	45,5635
433	568	5,9607	0,200	-0,7688	-2,22x10^{-16}	23,6043
3786	270	5,8814	0,409	-1,11x10^{-16}	-2,22x10^{-16}	35,3832
2702	217	4,7244	0,364	0	-5,55x10^{-16}	26,3062
2810	259	5,6466	0,316	-1,11x10^{-16}	0	28,8245
870	686	8,5318	0,200	-0,6754	-1,11x10^{-16}	33,7859

TABLE II. D RESULTS OF NEW SAMPLES WITH ANN

P (kgf)	*L (cm)*	ANN (10 neuron)	Error Metric Values for FPA		
		d (cm)	***MAE***	***MAPE***	***MSE***
171	551	4,3687	0,0847	1,9780	0,0072
1373	306	5,7872	0,0105	0,1819	0,0001
958	110	2,4948	0,1064	4,4569	0,0113
749	411	5,7955	0,0286	0,4954	0,0008
2043	701	11,4767	0,0293	0,2542	0,0009
433	568	5,8880	0,0727	1,2198	0,0053
3786	270	5,7367	0,1447	2,4605	0,0209
2702	217	4,7064	0,0180	0,3805	0,0003
2810	259	5,6852	0,0386	0,6840	0,0015
870	686	8,5527	0,0209	0,2452	0,0004
		Average	0,0554	1,2356	0,0049

TABLE III. T RESULTS OF NEW SAMPLES WITH ANN

P (kgf)	*L (cm)*	ANN (10 neuron)	Error Metric Values for FPA		
		t (cm)	***MAE***	***MAPE***	***MSE***
171	551	0,197	0,0026	1,3181	0,0000
1373	306	0,228	0,0288	14,3849	0,0008
958	110	0,265	0,0098	3,8375	0,0001
749	411	0,219	0,0198	9,8751	0,0004
2043	701	0,187	0,0128	6,3985	0,0002
433	568	0,209	0,0092	4,5756	0,0001
3786	270	0,479	0,0693	16,9100	0,0048
2702	217	0,408	0,0441	12,1022	0,0019
2810	259	0,373	0,0564	17,8151	0,0032
870	686	0,198	0,0011	0,5428	0,0000
		Average	0,0254	8,7760	0,0011

TABLE IV. MIN F(D,T) RESULTS OF NEW SAMPLES WITH ANN

P (kgf)	*L (cm)*	ANN (10 neuron)	Error Metric Values for FPA		
		Min f(d,t)	***MAE***	***MAPE***	***MSE***
171	551	17,2501	0,2855	1,6829	0,0815
1373	306	22,9529	0,0064	0,0279	0,0000
958	110	11,2577	0,5042	4,6883	0,2542
749	411	22,9484	0,1114	0,4878	0,0124
2043	701	45,7778	0,2143	0,4703	0,0459
433	568	23,3401	0,2642	1,1193	0,0698
3786	270	35,4033	0,0200	0,0566	0,0004
2702	217	26,3915	0,0854	0,3245	0,0073
2810	259	28,8227	0,0018	0,0061	0,0000
870	686	33,9598	0,1739	0,5147	0,0302
		Average	0,1667	0,9378	0,0502

TABLE 5. THE DESIGN CONSTRAINTS OF NEW SAMPLES WITH ANN

P (kgf)	*L (cm)*	g1	g2
171	551	-0,8737	-0,0443
1373	306	-0,3398	-0,1213
958	110	-0,0780	-0,1549
749	411	-0,6256	-0,1035
2043	701	-0,3946	**0,0766**
433	568	-0,7762	-0,0080
3786	270	-0,1231	-0,0802
2702	217	-0,1045	-0,0991
2810	259	-0,1570	-0,1694
870	686	-0,6744	-0,0019

6 Conclusions

The developed ANNs model for cost optimization of tubular columns is effective to predict close values to optimum results obtained by FPA base methodology. Generally, MSE values are so small for two design variables and objective functions. The difference between the predicted d values and optimum ones are between 0.18% and 4.46%. The differences of t values are between 1% and 18.04%. Only one of the predicted results have constraints violation.

In future, these types of ANNs models can be used to shorten the process of structural optimization problems. Also, long design calculations can be eliminated.

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