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Research Article

Metaheuristic algorithms in optimum design of reinforced concrete beam by investigating strength of concrete

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ABSTRACT

The locations of structural members can be provided according to architectural projects in the design of reinforced concrete (RC) structures. The design of dimensions is the subject of civil engineering, and these designs are done according to the experience of the designer by considering the regulation suggestions, but these dimensions and the required reinforcement plan may not be optimum. For that reason, the dimensions and detailed reinforcement design of RC structures can be found by using optimization methods. To reach optimum results, metaheuristic algorithms can be used. In this study, several metaheuristic algorithms such as harmony search, bat algorithm and teaching learning-based optimization are used in the design of several RC beams for cost minimization. The optimum results are presented for different strength of concrete. The results show that using high strength material for high flexural moment capacity has lower cost than low stretch concrete since doubly reinforced design is not an optimum choice. The results prove that a definite metaheuristic algorithm cannot be proposed for the best optimum design of an engineering problem. According to the investigation of compressive strength of concrete, it can be said that a low strength material are optimum for low flexural moment, while a high strength material may be the optimum one by the increase of the flexural moment as expected.

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1. Introduction

In structural systems, both tensile and compressive stresses occur under external loads. It is not possible to build these structural systems under tensile stresses using only brittle materials such as concrete. Although brittle materials are very useful in terms of compressive strength, they are inconsiderable in terms of tensile strength due to their small tensile strength. In this case, ductile materials like steel are quite important to meet tensile strength, but there are negative aspects like high costs and exposure to environmental conditions. Given the mentioned aspects of concrete and steel, the use of reinforced concrete structures is affordable, but the design of structure should be optimal and safe. Since two materials with different properties are used in the construction of reinforced concrete elements and the optimal cost structure is a non-linear problem, there is no optimal mathematical solution. In this case, numerical algorithms are quite useful.

In order to find the optimal design variables for reinforced concrete elements, metaheuristic algorithms are quite suitable. Genetic algorithms were proposed in different approaches. Coello et al. (1997) used the genetic algorithm in the optimum design of reinforced concrete beams. Rafiq and Southcombe (1998), benefited from the genetic algorithm for optimization of columns under the biaxial bending. Rajeev and Krishnamoorthy (1998) optimized reinforced concrete frame structures using a genetic algorithm-based method. Camp and et.al. (2003) used the genetic algorithm to optimize the reinforced concrete frame system, taking into account the slenderness

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of the columns. Ferreira et al. (2003) dealt with the optimization of T-profile beams according to different construction standards. In addition, the genetic algorithm, one of the classic metaheuristic algorithms, is used to achieve better results by combining it with other algorithms. As examples, combining genetic algorithm with simulated annealing optimization for continuous beams (Leps and Sejnoha, 2003) or combining genetic algorithm with Hook and Jeeves method for reinforced flat slab (Sahab et al., 2005) can be given.

Simulated annealing optimization is widely used in the optimum design of reinforced concrete elements such as the genetic algorithm. This algorithm is proposed for both cost optimization of reinforced concrete frames (Paya et al., 2008; Perea et al., 2008) and minimizing CO2 emission from reinforced concrete frames (Paya-Zaforteza et al., 2009). Similarly, Big Bang - Big Crunch Optimization was used to minimize CO2 emissions from reinforced concrete frames (Camp and Huq, 2013).

Optimization of reinforced concrete retaining walls is an important research area as it should be provided both structural and geotechnical rules. Simulated annealing optimization (Ceranic et al., 2001; Yepes et al., 2008), Harmony Search based algorithm (Kaveh and Abadi, 2011)), Big Bang - Big Crunch Optimization (Camp and Akin 2012) and Charged System Search Algorithm (Talatahari et al., 2012) for the optimization of reinforced concrete retaining walls can be shown as an example.

Harmony search algorithm is used to optimize the structural members such as continuous beams (Akin and Saka, 2010), T-shaped reinforced concrete (Bekdaş and Nigdeli, 2013), columns (Bekdaş and Nigdeli, 2014a; Nigdeli and Bekdaş, 2014a), frames (Bekdaş and Nigdeli, 2014b), walls (Nigdeli and Bekdaş, 2014b), cylindrical walls (Bekdaş, 2014; 2015) and biaxially loaded columns (Nigdeli et al., 2015). Tabu Search (Rama Mohan Rao and Shyju, 2010) and Artificial Bee Colony algorithm (Jahjouh et al., 2013) are the other algorithms, which are proposed to optimize the reinforced structural elements.

In this study, the optimum design of reinforced concrete beams was investigated. The metaheuristic algorithms, which are used in the optimization process, are the harmony search algorithm, bat algorithm and teaching-learning-based optimization. The results are given in five cases of the strength of concrete.

2. Methodology

In optimization of engineering problems, the goal is the determination of one or more design variables (x_i, i = 1,…, n) to bring the objective function to the most appropriate value. Design constraints which express equal equations ($h(x_i) = 0$) and unequal equations ($g(x_i) \leq 0$) in some cases are required to determine design variables. Optimal values of design variables are searched step by step with meta-heuristic algorithms that are inspired by natural events. As the first main design, the design variables are randomly selected within the limits set by the user. These design variables create a solution set. The number of solution sets created is equal to the population of the individuals and cases used in the simulation of algorithm. All solution sets are collected in a matrix and the objective function is calculated for each solution set. Design constraints are usually considered with a penalty function added to the objective function. After creating the first matrices with design variables, these matrices are updated according to the algorithm rules. The best solution is obtained with step-by-step updates.

In this study, three different metaheuristic algorithms were used to optimize the objective function. These are harmony search algorithm, bat algorithm and teaching-learning based optimization.

2.1. Harmony Search (HS)

Geem et al. (2001) developed harmony search algorithm which is a music-based algorithm. A musician plays popular notes in his memory to please his audience. New notes that are similar to these notes can also be played to impress the audience more. With this analogy, the harmony search algorithm is emerging for optimization problems. In the harmony search algorithm, the harmony memory matrix, which was originally created and contains harmony vectors, is revised step by step. Harmony vectors contain design variables which are defined by random numbers in the specified solution range. Harmony memory size (HMS) is the number of vectors in the harmony memory matrix. The harmony memory matrix is determined in two ways depending on the harmony memory consideration ratio (HMCR). As much as HMRC probability, new values are created around some of the existing values. In this case, a solution set covering a smaller area is used, and the ratio of this range to the whole area is determined by the pitch adjustment rate (PAR). Another new type of vector creation involves the use of the whole solution area. If the solution sets of the objective function are better than available solution sets, the results are replaced with the worst solution.

2.2. Bat Algorithm (BA)

The bat algorithm developed by Yang (2010) was inspired by the echolocation behavior of bats. Bats fly randomly to a position with fixed frequency, variable wavelength and loudness. Because of these properties, the design variables are included in the displacement vectors in the bat algorithm and the number of these vectors are equal to the bat population. Each displacement vector is modified at every step. Initial values are randomly determined from the solution set. Loudness and wave ratio (r_i) are the parameters that change in the algorithm process and determine the modification method. The basic code of the algorithm is presented in Table 1.

2.3. Teaching-Learning-Based Optimization (TLBO)

The analogy of a class is used in teaching-learning-based optimization method (Rao et al., 2011). This method guides two different types of design variables, the teacher and the learning process. Unlike other methods, these processes are applied in order without making a choice between the two processes. After a knowledge was imparted by the teacher, the students continue their development among themselves. Thus, all the members of the class are at a good level.

Table 1. Pseudo code of BA.

```
Objective Function f(x), x=(x1,.......,xd)T
determine the population (Xi) and speed (vi) (i=1,......,n) of bats
determine wave frequency (fi) at position xi
determine wave ratio (ri) and loudness (Ai)
condition (t < number of iteration)
    Get new results updating speed and locations by
    adjusting frequencies
      if (random number < ri)
      Choose one of the best results
      Create a local solution around selected results
      end
    Create a new solution by flying randomly
      if (random number < Ai and f(xi)<f(x*)
      Accept new result
      Increase ri and drop Ai
      end
    find the best solution (x*)
condition end
Print results
```

In the teacher process, the best result in the matrix is chosen as the teacher. It is provided to update the current result (X_{old}) and to approach the best result ($X_{teacher}$) by using random numbers (rand) as given in Eq. (1). In the equation, there is a new generated result (X_{new}) with the use of the mean of the existing variables (X_{mean}) and the teaching factor (TF), which can randomly take one or two as value.

$$X_{new} = X_{old} + rand(X_{teacher} - TFX_{mean}) \quad (1)$$

In the learning process, new results are obtained using two random (j and k) results, and only good results are updated. Mathematical expression of this process is shown in Eq. (2).

$$X_{new} = X_{old} + rand(X_j - X_k) \quad (2)$$

3. Numerical Examples

In the numerical examples, the design having the optimum material cost, including concrete and steel bar for reinforced concrete (RC) beams under the effect of the different bending moment (250 kNm and 500 kNm) are investigated. Also, the effect of different compressive strength of concrete such as 20 MPa, 25 MPa, 30 MPa, 35 MPa and 40 MPa. The cost difference for 5 MPa increase of strength is taken as 5 \$/m^3.

The design variables of the problem are presented in Fig. 1 and the design constants and ranges of design variables for optimization problem are shown in Table 2.

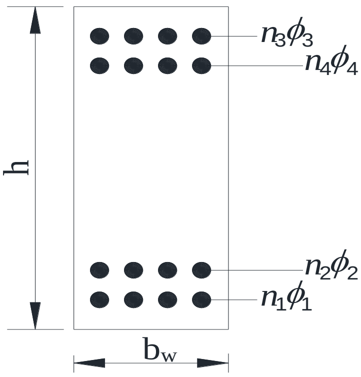

Fig. 1. Design variables of RC beam.

Table 2. Design constants for RC beam.

Design constant	Value
Concrete cover (mm)	35
Maximum aggregate diameter (mm)	16
Compressive strength of concrete (MPa)	20-40
Yield strength of steel (MPa)	420
Stirrup diameter (mm)	10
Unit concrete cost (\$/m^3)	30-50
Unit steel cost (\$/ton)	400
Range of longitudinal steel bars (mm)	10-30
Range of beam breadth (b) (mm)	250-400
Range of beam height (h) (mm)	300-500

In the study, the reinforcement design is done according to rules of ACI 318: Building code requirements for structural concrete and commentary (2005).

The optimization process is continued as long as the difference between the best and worst result is more than 2%, and this condition is stopping criteria of the optimization problem. The optimum results employing HS, BA and TLBO algorithms are summarized in Tables 3-5 for selected cases.

Table 3. Optimum results for 250 kNm and 20 MPa strength of concrete.

	HS	BA	TLBO
h (mm)	500	500	500
b_w (mm)	250	300	300
ϕ_1 (mm)	26	22	22
ϕ_3 (mm)	16	30	10
n_1	3	4	4
n_3	0	0	0
ϕ_2 (mm)	12	10	10
ϕ_4 (mm)	30	12	10
n_2	4	4	4
n_4	0	0	0
Optimum cost (\$/m)	10.12	10.21	10.43

Table 4. Optimum results for 500 kNm and 20 MPa strength of concrete.

	HS	BA	TLBO
h (mm)	500	500	500
b_w (mm)	400	400	400
ϕ_1 (mm)	26	26	26
ϕ_3 (mm)	14	26	18
n_1	6	6	6
n_3	3	2	4
ϕ_2 (mm)	14	10	10
ϕ_4 (mm)	30	30	10
n_2	6	6	6
n_4	0	0	0
Optimum cost ($/m)	20.23	20.69	20.56

Table 5. Optimum results for 500 kNm and 35 MPa strength of concrete.

	HS	BA	TLBO
h (mm)	500	500	500
b_w (mm)	300	350	350
ϕ_1 (mm)	30	28	28
ϕ_3 (mm)	12	24	10
n_1	4	5	5
n_3	3	0	0
ϕ_2 (mm)	26	14	14
ϕ_4 (mm)	24	12	10
n_2	2	4	4
n_4	0	0	0
Optimum cost ($/m)	19.85	19.32	19.32

According to the results for the 250 kNm flexural moment for 20 MPa compressive strength, single reinforced solution is optimum. Whereas double reinforced design is optimum for 500 kNm for the same concrete class. By the increase of the concrete strength, singly reinforced design become also optimum for 500 kNm flexural moment. In Table 5, HS approach result is a little expensive than the others, and doubly reinforced design is found as optimum with a smaller cross-sectional area.

4. Conclusions

In the study, three different algorithms i.e. HS, BA, TLBO are used for optimization of the RC beam member and the optimum results are compared. The optimum cost values for two flexural moment cases are shown as bar diagrams in Figs. 2 and 3 for comparison of algorithms and the best choice of the compressive strength of concrete.

In this study, a penalty function is not used in case the design constraints are not provided. Instead, variables are randomly generated until all design constraints are provided at each step. Therefore, optimum results are effective and fast.

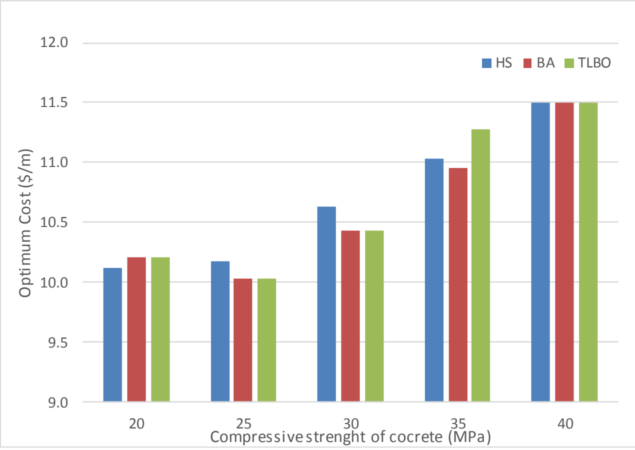

Fig. 2. The optimum costs for 250 kNm flexural moment.

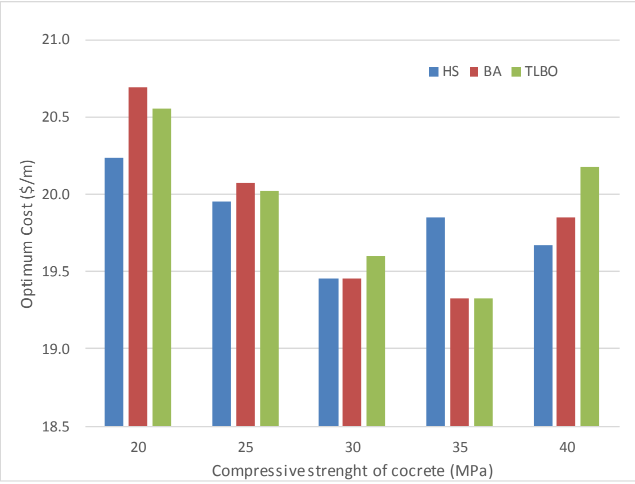

Fig. 3. The optimum costs for 500 kNm flexural moment.

As seen in Fig. 2, the best case for 250 kNm flexural moment value is 25 MPa compressive strength. By the increase of the moment, 35 MPa compressive strength has the minimum cost due to singly reinforced optimum design without compressive reinforcement bars. If the compressive strength is lower than that value, compressive reinforcement bars are needed.

It is clearly seen that there is no specific algorithm which is dominantly distinguished than the others. This situation proves that even in different parameters cases of the same optimum design problem, the best algorithm choice may be different.

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