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Minimum weight design of reinforced concrete beams utilizing grey wolf and backtracking search optimization algorithms

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ABSTRACT

In this study, optimal weight design of a reinforced concrete beam subjected to various loading conditions is investigated. The purpose of the optimization is to attain the minimum weight design of the reinforced concrete beam under distributed and two-point loads. The design problem is handled under three different design load cases. The two-point loads are affected on beam-to-beam connection nodes of reinforced concrete beams. Thus, while the magnitudes of distributed load and two-points load are remained constant, the distances between two-points loads are taken as 2m, 3m and 4m, respectively. The width and height of the rectangular cross-section of the concrete beam, and the diameters of the longitudinal and confinement steel rebars are treated as design variables of the optimum design problem. The design constraints of the optimization problem consist of the geometric constraints and necessities of the Turkish Requirements for Design and Construction of Reinforced Concrete Structures (TS500), and Turkish Building Earthquake Code (TBEC). As two novel metaheuristics, grey wolf (GW) and backtracking search (BS) optimization algorithms are selected as optimizers. Both algorithms are independently operated five times for three different design problems. Thus, the obtained results are examined statistically to compare in accordance with algorithmic performances. The optimal findings from optimization algorithms show that the GW algorithm is a little bit more robust on the exploitation phase, while the BS algorithm is stronger on the exploration phase. Moreover, it can be deducted from optimal beam designs that the GW algorithm is more viable to minimize reinforced concrete beam design.

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1. Introduction

The engineering design is generally based on the requirements of safety, economy and aesthetics, respectively. In this context, it is not enough for the design to fulfill the safety requirements alone. However, when all these requirements are considered, a hard to solve engineering design problem is confronted. Moreover, in some engineering design problems, some preliminary assumptions must be made in order to operate the required mathematical computations. For example, in order to design a steel structural member, first of all, the design loads acting on this member must be known. Hence, the internal forces of the element are calculated, and then the profile to be assigned to the structural element is selected according to these calculated loads. Yet, the design loads on the structural element are directly related to the dead load and the section to be selected (Tunca 2022). In the design of a reinforced concrete beam, to calculate the area of longitudinal steel rebars, first of all, the cross-sectional dimensions of the reinforced concrete beam should be instinctively selected. In some cases, the selected section sizes are insufficient and/or excessive (Coello et al. 1997; Hasan et al. 2019). Practically, the required dimensions are tried to be found by trial-and-error method. So, new calculation methods are needed to obtain the optimal design (Abubakar et al. 2021). At this point, the stochastic optimiza-

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tion methods come into the picture. These methods, tackle with objective or objectives, design variables, and design constraints of handled engineering design problem (Aydogdu 2016). In structural engineering, the objectives can be categorized as minimizing the cost of a structure while maximizing the structural responses under external loads (Jin et al. 2021). The design variables can be related to material property and geometry of the structure (Carbas et al. 2021). Some constraints are needed to ensure that the structures or structural elements are serviceable and comply with the relevant practical structural provisions. These are often selected as displacement, drift, or strength (Aydogdu 2016).

In this study, it is aimed to minimize weight of a single span reinforced concrete beam which is subjected to three different load cases. The height and width of the reinforced concrete beam, and the diameters of the longitudinal and confinement steel rebars are considered as design variables. Additionally, the optimum designs are intended to comply with Turkish Requirements for Design and Construction of Reinforced Concrete Structures (TS500 2000), and Turkish Building Earthquake Code (TBEC 2018). The constraints of the design optimization problem consist of the geometric constraints and necessaries of these requirements.

There are various optimization techniques applied to accomplish optimum designs of reinforced concrete structures and/or elements (Lu et al. 2021; Fahr et al. 2022). In this study, metaheuristic optimization methods are utilized as optimizer that do not require any derivative operations and initial gradient information (Kazemzadeh Azad and Aminbakhsh 2022). These methos offer designers convenience and ease in solving complex engineering design problems (Peng et al. 2022). Moreover, the stochastic based metaheuristic methods are also suitable for design problems involving nonlinear material and/or geometry. However, the solution of these problems is time consuming and it cannot be claimed that the obtained results are global optimum. In these kinds of problems, the design variables must be calculated as discrete ones (Erdal et al. 2016). In instance, the standard diameters of steel rebars are practically taken as 8mm, 10mm, or 12mm. Thus, to produce an optimally designed reinforced concrete beam, the selection of the steel rebars must be made amongst these values.

From past to now, numerous stochastic based metaheuristic optimization methods have been developed. Genetic algorithm (Goldberg and Holland 1988), harmony search method (Geem et al. 2016), particle swarm optimization (Perez and Behdinan 2007), firefly algorithm (Yang 2010) are some examples of so-called classical ones. To overcome their shortcuts and to enhance their algorithmic performances in finding the optimum results, so many brand-new stochastic optimization algorithms have been emerged day by day. The polar optimization algorithm (Chen et al. 2022), human felicity algorithm (Verij kazemi and Fazeli Veysari 2022), trees social relations optimization algorithm (Alimoradi et al. 2022) are the latest examples of novel metaheuristic optimization techniques. In this study, the grey wolf (GW) (Mirjalili et al. 2014) and backtracking search (BS) (Civicioglu 2013) optimization algorithms that are verified as successful to reach optimum results in the many engineering design problems, are executed. Both algorithms are tested on reinforced concrete beam design problems subjected to various loading conditions. Thus, both the optimum designs of reinforced concrete beams are obtained and the performances of two innovative optimization algorithms in obtaining optimum results are compared over the considered design problems.

The sections of the manuscript can be summarized as follows;

- In the Introduction section, the general concept of the study is defined.
- The practical design rules of the reinforced concrete beams are given in the second section.
- In the third section, the utilized stochastic based metaheuristic optimization methods are described.
- The design examples and obtained solutions and results are exhibited in the fourth section.
- The principal conclusions are presented in the fifth section.

2. Design Rules of Reinforced Concrete Beams

The design of a reinforced concrete beam having minimum design weight is considered as the objective of the optimization problem. The general illustration of the reinforced concrete beam design problem is given in Fig. 1. In Eq. (1), the $\boldsymbol{I^T}$ vector consists of sequence numbers of the height and width of the reinforced concrete beam, and diameters of the longitudinal and confinement steel rebars. Thus, it includes four different design variables.

$$\boldsymbol{I^T} = [I_1, I_2, I_3, I_4] \quad (1)$$

The weight of the reinforced concrete beam can be determined multiplying the volume and the unit weights of the components as shown in Eq. (2).

$$W = \rho_c\, h\, b_w L_b + \rho_s \left(n \frac{\pi \emptyset^2}{4} L_l + n_c \frac{\pi \emptyset_e^2}{4} L_c \right) \quad (2)$$

Here, ρ_c and ρ_s are the unit weights of the concrete and steel. The h and b_w are the height and width of the reinforced concrete beam. L_b, L_l and L_c represent the lengths of the beam, longitudinal and confinement steel rebars, respectively. $\emptyset$ and $\emptyset_e$ are diameters of the longitudinal and confinement steel rebars, and n and n_c are total number of these.

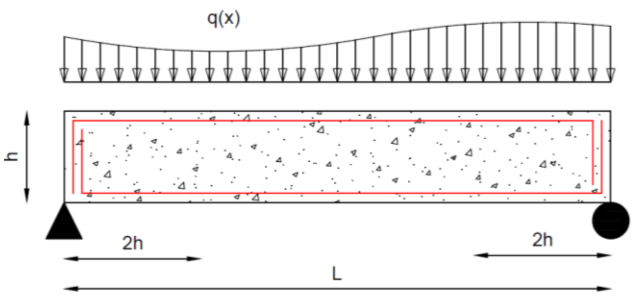

Fig. 1. The reinforced concrete beam.

In the first part of design problem, the height and width of the reinforced concrete beam should be determined. Here, if these are chosen small, the cross-section of the concrete part of the beam may be insufficient. If these are chosen large, it will be an uneconomical engineering design. The calculation of reinforced concrete beams is based on the assumption that the concrete part of the beam bear only compression loads. Therefore, the location of the neutral axis must be found. The distribution of compression loads in the cross-section is not uniform as seen Fig. 2a. However, for ease of calculation, the length of the neutral axis (c distance), is converted to uniform by multiplying the k_1 factor (Fig. 2b).

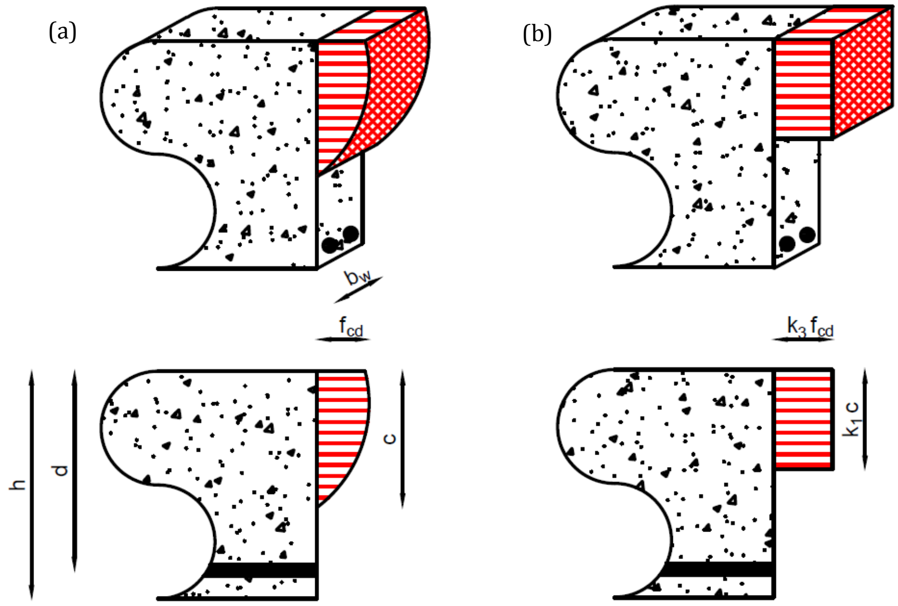

Fig. 2. Compressive stress distribution on the cross-section of the reinforced concrete beam: (a) Real distribution; (b) Uniform distribution.

The height of the effective compression area can be calculated using Eq. (3).

$$k_1 c = d - \sqrt{d^2 - \frac{2M_d}{k_3 f_{cd} b_w}} \tag{3}$$

Here, $k_1 c$ is location of reduced neutral axis, d is effective height, M_d is the design moment, and $k_3 f_{cd}$ is reduced concrete design strength. In such a reinforced concrete beam, the compressive force carried by the concrete and the total tensile force carried by the steel rebars should be equal. So, the total area of the longitudinal reinforcement (A_s) is generated easily via Eq. (4).

$$A_s = \frac{M_d}{f_{yd}\left(d - \frac{k_1 c}{2}\right)} \tag{4}$$

The number of longitudinal steel rebars (n) is determined through Eq. (5). In the mentioned equation, the *int* represents the integer transformation function. Here, the diameter of the longitudinal reinforcement is predetermined by designer.

$$n = int\left(\frac{A_s}{\frac{\pi \emptyset}{4}}\right) + 1 \tag{5}$$

The length of the longitudinal steel rebars is required to determine the quantities. This is determined according to Fig. 1.

The confinement steel rebars reinforce the beam to the shear loads. These are handled in two regions as confinement zone and remaining zone. The shear force at a distance d from the column face is considered for confinement zone. In the other, this distance is taken as $2h$. Before the calculation of confinement steel rebars, the cross section of the reinforced concrete beam is checked utilizing Eq. (6).

$$V_{d-\max} = 0.85\, b_w h \sqrt{f_{ck}} \tag{6}$$

Here, V_{d-max} is the maximum designable shear carrying capacity of the reinforced concrete beam. The characteristic pressure strength of the concrete is represented as f_{ck}. The critic shear force is calculated considering the unreinforced condition of the concrete beam using Eq. (7).

$$V_{cr} = 0.65\, f_{ctd}\, b_w d \tag{7}$$

Here, V_{cr} is critic shear force and f_{ctd} is the tension design strength of the concrete. The shear force carried by the steel rebars is calculated via Eq. (8).

$$V_w = V_d - 0.8\, V_{cr} \tag{8}$$

The minimum amount of steel rebar determined by structural specifications can be calculated from Eq. (9). Here, the double-armed confinement steel rebar is utilized for beam modelling since this kind of confinement steel rebars are practically implemented in real-life reinforced concrete beam applications too often.

$$S_c = min\begin{pmatrix} \frac{A_{sw} f_{ywd} d}{V_w} \\ \frac{h}{4} \\ 8\emptyset \\ 150mm \end{pmatrix} \tag{9}$$

Here, S_c is the distances between two confinement steel rebars. In the remaining zone, this value is symbolized with S_o, and determined via Eq. (10).

$$S_o = min\begin{pmatrix} \frac{A_{sw} f_{ywd} d}{V_w} \\ if\ V_d \leq 3V_{cr}\ then\ S_o = \frac{d}{2} \\ if\ V_d > 3V_{cr}\ then\ S_o = \frac{d}{4} \end{pmatrix} \tag{10}$$

The obtained S_c and S_o are used to determine the total number of the confinement steel rebars (n_c).

$$n_c = int\left(\frac{4d}{S_c} + 1\right) + int\left(\frac{L-4d}{S_c} + 1\right) \tag{11}$$

The lengths of the confinement steel rebars are calculated considering Fig. 3. As the hook length of the confinement steel rebars, the biggest one of $6\emptyset_e$ and 8 cm is accepted as the minimum value.

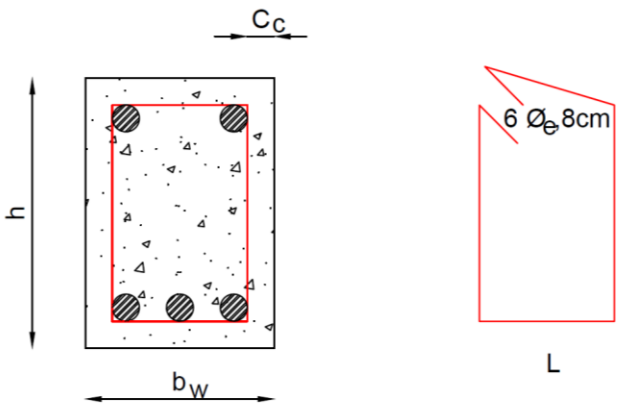

Fig. 3. Confinement rebars of reinforced concrete beam.

Finally, it should be checked that the determined steel rebars fits into the cross section of the reinforced concrete beam as illustrated in Fig. 4. For this aim, Eq. (12) is utilized.

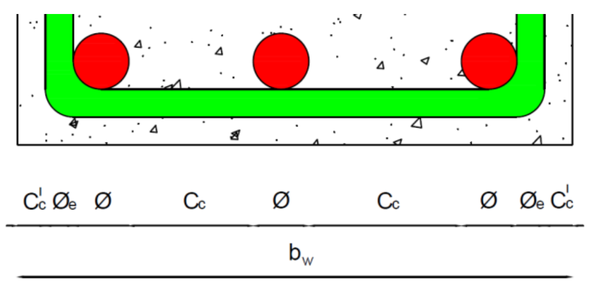

Fig. 4. Settlement of reinforcements.

$$b_w \geq 2C_c' + 2\emptyset_e + n\emptyset + (n-1)C_c \tag{12}$$

Here, C_c' is the thickness of concrete cover, and C_c is the distance between longitudinal steel rebars.

3. Optimization Methods

In this study, two recent metaheuristics, namely grey wolf (GW) and backtracking search (BS) optimization algorithm are utilized as optimizers to minimize the design weight of the reinforced concrete beam.

3.1. Backtracking search (BS) algorithm

Backtracking search (BS) algorithm is encoded by Civicioglu in 2013. BS has only a single control parameter, and simple and effective algorithmic structure. It consists of five main steps such as initialization, selection-I, mutation, crossover, and selection-II. In the first step, the population size, the total number of dimensions, the lower and upper bounds of the design variables are defined. Then, initial population is obtained utilizing Eq. (13).

$$P_{i,j} \sim U(low_j, up_j) \tag{13}$$

Here, U symbolizes uniform distribution probability and, $P_{i,j}$ is possible solution value.

The historical population is generated in the selection-I step. When initial P_{old} is generated, this based on randomization as in P. Then, Eq. (14) is utilized for the other iterations.

$$\text{if } a < b \text{ then old}P \coloneqq P|a, b \sim U(0,1)| \tag{14}$$

In Eq. (14), a and b are generated randomly between 0 and 1. If b is bigger than a, the element of the P_{old} is shifted with the element of P. Otherwise, the element value of P_{old} is saved as memory of BS. Then, the order of the elements in P_{old} is permuted using Eq. (15).

$$\text{old}P \coloneqq Permuting(\text{old}P) \tag{15}$$

In the mutation step, the form of the trial population *Mutant* is obtained via Eq. (16).

$$Mutant = P + F\ (\text{old}P - P) \tag{16}$$

Here, F represents an adjusting coefficient of the search direction amplitude that is randomly generated in each iteration. The trial population is shaped final form in crossover step. The crossover step has two main stages. Initially, the binary integer-valued matrix (*map*) is created based on randomization. The *map* consists of the 0 and 1 values. Here, the dimensions of the T, P, and *map* are same. On condition that, element of the *map* is 0, element of T is saved. Otherwise, the element of the T is manipulated with the element of the P in same matrix index. In case the values exceed the upper and lower boundaries, the limit values are assigned instead of these values.

Finally, the global minimum value is checked in selection-II step. If the old *global minimum value* that is better than the fitness of best vectors of P (P_{best}), it is saved. Otherwise, The P_{best} is saved as the *global minimum value*.

3.2. Grey wolf (GW) algorithm

Grey wolf (GW) algorithm was encoded by Mirjalili et al. (2014). It imitates the social and hunting behaviors of grey wolves (Canis lupus). The grey wolfs have hierarchical characteristics. They move together to hunt preys. There are three dominant grey wolf named alpha (α), beta (β), and omega (ω). The domination is getting increase from ω to α.

In a hunting, the grey wolves group encircles the prey at the beginning. This behavior of grey wolves is operated via Eqs. (17) and (18).

$$\vec{D} = \left|\vec{C}\vec{X}_p(t) - \vec{X}(t)\right| \quad (17)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}\vec{D} \quad (18)$$

Here, the number of iterations is symbolized with t. The $\vec{X}$ and $\vec{X}_p$ represent the locations of grey wolves and prey, respectively. The expression of $\vec{A}$ and $\vec{C}$, which are the coefficient vectors, are given in Eqs. (19) and (20).

$$\vec{A} = 2\,\vec{a}\vec{r}_1 - \vec{a} \quad (19)$$

$$\vec{C} = 2\,\vec{r}_2 \quad (20)$$

Here, $\vec{r}_1$ and $\vec{r}_2$ are randomly generated between 0 and 1. In the iterative process, $\vec{a}$ is linearly reduced 2 to 0.

The hunting starts after the encircling process. The most dominant gray wolf α manages the hunt. However, sometimes β and ω also contribute to management. So, the positions of the grey wolves are relocated consistent with the results of α, β, and ω. Eqs. (21) to (23) are performed for this purpose.

$$\vec{D}_\alpha = \vec{C}_1\vec{X}_\alpha - \vec{X}, \quad \vec{D}_\beta = \vec{C}_2\vec{X}_\beta - \vec{X}, \quad \vec{D}_\delta = \vec{C}_3\vec{X}_\delta - \vec{X} \quad (21)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1(\vec{D}_\alpha), \qquad \vec{X}_2 = \vec{X}_\beta - \vec{A}_2(\vec{D}_\beta),$$
$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3(\vec{D}_\delta) \quad (22)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1+\vec{X}_2+\vec{X}_3}{3} \quad (23)$$

The hunting step of the algorithm is completed by terminating the repositioning. Here, the $\vec{A}$ starts to decrease due to the decrease in $\vec{a}$. The reduction of the value of $\vec{A}$ impress the gray wolves to hunt.

4. Design Examples

Three reinforced concrete beams having three different mid-spans (a distance) are considered as design examples as showed in Fig. 5. All of them has 6m of total span length. They are placed on columns having 400 mm wide at its supports. The yield strength of the concrete and steel rebars are taken as 25 MPa and 420 MPa, respectively. The safety factors are considered as 1.5 for concrete and 1.15 for steel. The unit weights of them are taken as 24 kN/m^3 and 76.98 kN/m^3, respectively. The distributed loads of 25kN/m and two-point loads of 100kN are assigned as design loads as shown in Fig. 5. Here, the two-point loads represent the beam connection joints, and the distance between them varies from structure to structure. So, the distance between two-points loads (a distance) is taken as 2m, 3m, and 4m for reinforced concrete beams.

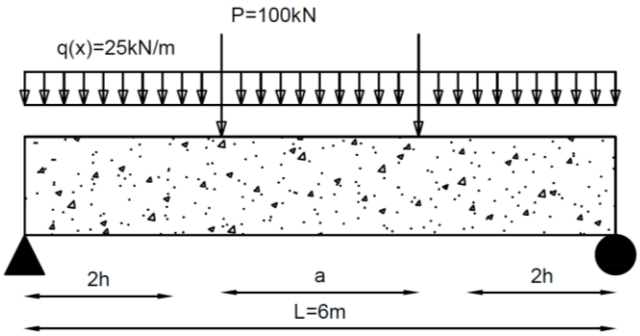

Fig. 5. General scheme of reinforced concrete beam.

The minimum design weight is considered as objective. Before solving such a concrete beam design problem, the b_w and h values should be estimated. So, these are taken as first two design variables. After their estimation, the required amount of steel rebars can easily be calculated. However, the selection of the diameters of rebars is also needed to complete the design. Thus, the diameter of longitudinal steel rebars and confinement steel rebars are also treated as design variables. To obtain viable design, the structural necessities for design constraints are taken from Turkish Requirements for Design and Construction of Reinforced Concrete Structures (TS500 2000), and Turkish Building Earthquake Code (TBEC 2018). As addition to these, the geometric constraint is considered as the steel rebars fits into the cross section of the reinforced concrete beam. The population size is taken as 20 for both algorithms. The adjusting coefficient (F) of the BS algorithm is considered as 3 and the (α) parameter of the GW algorithm is linearly reduced from 2 to 0. The number of iterations is taken as 500 in each optimization process. So, the total number of required structural analyses is taken as 500×20=10000.

The optimum designs of the reinforced concrete beams are independently obtained via GW and BS algorithms as given in Table 1. From this table, it is clearly seen that there are no any violations on design constraints in optimally designed beams. Besides, the most dominant design constraint is the geometric constraint which checks whether steel rebars fits into the cross section of the reinforced concrete beam or not. Moreover, in order to statistically evaluate the attained optimal design solutions, each algorithm is executed on the same design example for five times. Among these, the minimum design weight histories of the algorithms are illustrated in Fig. 6. In the first design example, which has 2 m distances between two-points loads (a=2m in Fig. 5), the GW and BS algorithms attain the same optimal design weight of 17.317 kN. However, the GW and BS algorithms require 377 and 221 structural analyses to reach minimum design weights, respectively. It means that in the first design example, the BS algorithm require 70.59% structural analyses than the GW algorithm. In the second design example, which has 3m distances between two-points loads, the GW algorithm does not only find a lighter beam design, but also converge 21.37% faster than BS algorithm since it needs only 234 structural analyses. In the third and final design example, which has 4 m distances between two-point loads, both metaheuristic optimization algorithms show almost identical algorithmic performances. They generate same minimum optimal design weight of 14.534 kN. But to accomplish this design weight the GW algorithms show 10% faster convergence rate than BS algorithm.

Furthermore, the accomplished statistical results are tabulated in the Table 1. Here, the worst weight, the average weight, and the standard deviation values are presented to illustrate the dispersion between optimal design weights attained from five different initial populations via GW and BS optimization algorithms. The relatively lower standard deviations indicates that the obtained minimum design weights are tend to be smoothly scattered around the average weights and the box-plots of these executions are illustrated in Fig. 7. From these findings, it can be deduced that although the BS algorithm seems as more successful in the design of reinforced concrete beams with a distance of 2 m between two-points loads, the statistical data indicates that the GW algorithm puts forward more stable and more consistent performance in attaining the final optimum design of reinforced concrete beams.

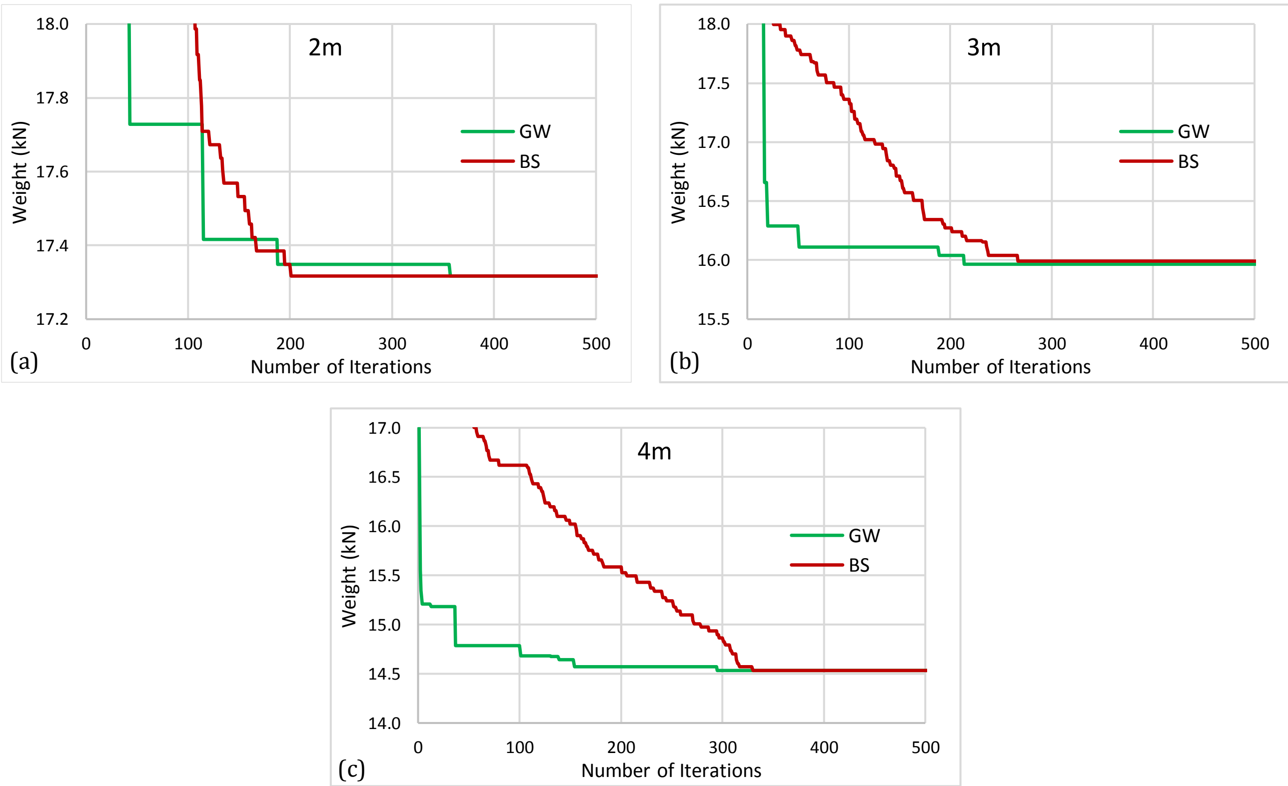

Fig. 6. Design histories of reinforced concrete beams having a) 2m; b) 3m; and c) 4m between two-point loads.

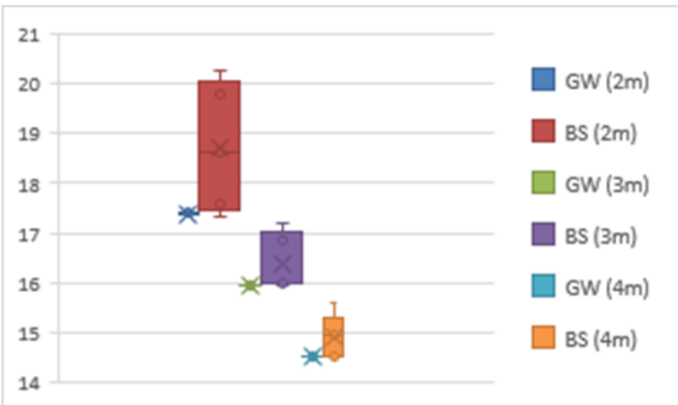

Fig. 7. Box-plots of obtained optimum reinforced concrete beams.

Table 1. Optimum design results of reinforced concrete beams.

Distance between two-point loads	2 m		3 m		4 m	
Algorithm	BS	GW	BS	GW	BS	GW
b_w (mm)	252	252	251	250	250	250
h (mm)	468	468	433	434	394	394
$Ø_e$	8	8	8	8	8	8
Ø	40	40	38	38	38	38
$g(1)$	-0.439	-0.439	-0.430	-0.431	-0.490	-0.490
$g(2)$	-0.872	-0.872	-0.872	-0.872	-0.872	-0.872
$g(3)$	0.000	0.000	-0.020	-0.016	-0.016	-0.016
Weight (kN)	17.317	17.317	15.992	15.966	14.534	14.534
No. of required structural analyses	221	377	287	234	350	315
Worst weight (kN)	20.265	17.394	17.189	15.966	15.596	14.534
Standard deviation	1.307	0.035	0.578	0.000	0.435	0.000
Average weight (kN)	18.718	17.379	16.395	15.966	14.916	14.534

5. Conclusions

The optimum design of reinforced concrete beams having three different mid-span lengths between two-point loads as 2 m, 3 m, and 4 m are obtained. Finding the minimum design weights of the beams are taken as main objective. When the design weights of the reinforced concrete beams are calculated, the confinement steel rebars are considered as well as the weight of the concrete and longitudinal steel rebars. The design variables are set as discrete values in order to make possible of fabrication the designed beams. To do this, the structural necessities from Turkish Requirements for Design and Construction of Reinforced Concrete Structures (TS500 2000), and Turkish Building Earthquake Code (TBEC 2018) are considered. So, totally three optimum design problems are handled utilizing the grey wolf (GW) and backtracking search (BS) optimization algorithms for this purpose. Thus, both the optimum designs of reinforced concrete beams are found and the performances of metaheuristic optimization algorithms are compared. Both algorithms are independently operated five different times for each design example. By this means, the obtained results are statistically examined and discussed. The principal conclusions of this study can be itemized as in the following bullet points:

- The GW and BS algorithms can robustly be used as the design optimizer to minimum weight design of reinforced concrete beams.
- The GW and BS algorithms accomplish identical minimum design weight of 17.317 kN for design example having 2 m distance between two-point design loads. However, to produce this optimum design weight the BS and GW algorithms require 221 and 377 structural analyses, respectively. So, BS algorithm computationally performs 70.59% better than GW algorithm for the first design example. Yet, in other design examples, the algorithmic performance of the GW algorithm is better than BS algorithm.
- The design history graphs prove that while BS algorithm has better exploration capacity, the GW algorithm has powerful in exploitation capacity.
- Finally, the statistical analyses illustrate the supremacy of GW algorithm in finding the minimum design weights of the reinforced concrete beams.

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Conflict of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this manuscript.

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