CHALLENGE JOURNAL OF CONCRETE RESEARCH LETTERS 15 (4) (2024) 134–141

Challenge Journal of Concrete Research Letters

Research Article

Optimum design of reinforced concrete beam sections with JAYA algorithm

Yasin Duysak [a], Sinan Melih Nigdeli [a,*], Gebrail Bekdaş [a]

[a] *Department of Civil Engineering, İstanbul University-Cerrahpaşa, 34320 İstanbul, Türkiye*

ABSTRACT

Section design is an important process for designing reinforced concrete structures because of the existence of factors such as bearing capacity and cost. After defining the initial cross sections for reinforced concrete elements, reinforcement amounts are calculated within the framework of certain rules and regulations. In the classical method, optimum cost and reliable structure can be designed by trial and error. Designing with the classical method is quite time-consuming. As in different fields, metaheuristic algorithms are employed to civil engineering applications to reach the optimum solution. In this study, unlike other examples from the literature, the optimum cost design of reinforced concrete beam cross-section was done, adding torsional moment to bending moment and effects of shearing force through the use of the JAYA algorithm. The optimum cost design of a reinforced concrete beam section under the effects of torsional moment, bending moment and shear force is performed. The design is done according to the rules specified in ACI 318 (Building code requirements for structural concrete), as it is well-known and used in many international projects. For the purpose of this study, cross-sections of 10 different reinforced concrete beam cross-sections were designed under 5 different loads for 2 different concrete classes through MATLAB software, with the aim of finding the optimum beam cross-section. A reinforced concrete beam is designed under different torsional loads and for different concrete classes and it is aimed to find the optimum beam cross-section. It shows the effect of torsional force on reinforced concrete beam cross section and reinforcement by using different torsional loads. It was observed that the algorithm used tends to approach the optimum result, increasing the area of concrete with lower unit cost or reducing the distance between stirrups. It was concluded that Jaya algorithm performs effectively with respect to optimizing reinforced concrete beams. The algorithm used can be applied to different reinforced concrete elements.

ARTICLE INFO

Article history:
Received 27 May 2024
Revised 25 July 2024
Accepted 19 August 2024

Keywords:
Beam section
Jaya algorithm
Section optimization
Torsional moment

1. Introduction

The design of reinforced concrete structural elements is a complex and important process in engineering practice. In this process, civil engineers determine various initial element sizes in structural design and these sizes form the basic reference points for reinforcement design. One of the important objectives of the engineer is to solve the design economically. However, the first choice does not always guarantee an economical design because factors such as economic design, durability and safety of the structure must be considered. Therefore, it is important to experiment with different element sizes to get a better design. It is important to know about the behaviors of engineering structure elements. Studies were conducted in connection with behaviors of structure elements in many fields. El-Sayed and Shaheen (2020) experimentally and analytically examined the behaviors of reinforced concrete beams containing recycled steel fiber and recycled wheat straw ash-based geo-

---

* *Corresponding author*. Tel.: +90-212-473-7070 ; E-mail address: melihnig@iuc.edu.tr (S. M. Nigdeli)

ISSN: 2548-0928 / DOI: https://doi.org/10.20528/cjcrl.2024.04.003

polymer. El-Sayed (2019) conducted a study on increasing beams' resistance strengths through the addition of industrial lathe wastes to reinforced concrete beams. Ghali et al. (2024) conducted a research examining the behavior of beams with reinforced concrete rectangular beams as reinforced with metallic and non-metallic fibers.

For an experienced engineer, several factors influence the economic design of reinforced concrete elements. These factors include various elements such as material properties of the structural elements, load carrying, structural integrity and aesthetics. However, it is not possible to try thousands of different combinations of sizes with the classical method of trial and error. Therefore, a process called optimization is used to find the best design that satisfies all design constraints. Optimum design methods have been proposed for different reinforced concrete elements and it is possible to apply these methods by using mathematical methods. Some methods have been developed for the optimum solution of engineering problems. Among these methods, optimization algorithms have an important place. Therefore, metaheuristic algorithms are a suitable option to perform a practical optimization. Metaheuristic algorithms are used to solve complex optimization problems by combining different search strategies and algorithm techniques. These algorithms can be tuned to suit the solution of a specific problem and are usually implemented through computer-based software. Thus, it may be possible to obtain optimum designs in large and complex reinforced concrete construction projects.

Consequently, the design of reinforced concrete elements is carried out with a combination of both engineering skill and mathematical optimization techniques. In this process, using an experienced engineering approach and appropriate optimization methods, it is possible to build economical, durable and safe structures. This can save cost and time in building projects, while at the same time improving the performance and quality of the structures.

Many heuristic and metaheuristic algorithms are used in civil engineering. One of the metaheuristic algorithms used in civil engineering is the artificial bee colony (ABC) algorithm. Jahjouh et al. (2013) in the optimal cost design of continuous beams. Tapao and Cheerarot (2017) used artificial bee colony (ABC) algorithm in cost design of reinforced concrete frame systems, Sönmez (2011) in weight minimization and optimum cost design of truss systems, Öztürk and Durmuş (2013) in optimum cost design of reinforced concrete columns.

Çakıroğlu et al. (2021a) conducted a study on the stacking of composite laminates with carbon fiber reinforcement with harmony search algorithm. Çakıroğlu et al. (2020a) used harmony search algorithm for the design of connection slabs under effect of cutting twisting and lateral twisting torsion and tried to find minimum cross-section areas that are to meet lateral torsion twisting loan and cutting tensions and to reduce the cost. Çakıroğlu et al. (2020b) used harmony search algorithm in order to find the highest possible twisting load, keeping the cost and weight of rectangular laminated composite plates at a minimum. Çakıroğlu et al. (2021b) made use of harmony search algorithm to reduce CO_2 emission which also offers the best performance in the design of steel columns with concrete filling. Bekdaş et al. (2022a) used harmony search algorithm for optimum design of cylindrical walls and created a database using 7744 samples and machine learning models were developed based on such database. Bekdaş et al. (2022b) prepared 3125 different data samples for the design of reinforced concrete circular columns and for their optimum cost and ensured that machine learning models focusing on data were developed. Çakıroğlu et al. (2023a) created 40569 data sets using harmony search algorithm for the design of console shoring retaining walls and worked on machine learning techniques.

Another algorithm used in the optimal design of reinforced concrete elements is the teaching-learning based optimization (TLBO) algorithm, which is inspired by the two different stages of training developed by Rao et al. (2011). Kayabekir et al. (2020), Temur and Bekdaş (2016), Bekdaş and Temür (2017), and Öztürk et al. (2020) used the teaching-learning based optimization (TLBO) algorithm for the design and cost optimization of retaining walls; Niğdeli et al. (2018) for the design and optimum cost of reinforced concrete single foundations, Dede and Ayvaz (2015) for shape and size optimization of truss systems and elements, Bekdaş and Niğdeli (2016) for cost optimization of reinforced concrete columns of different heights.

Another algorithm used in structural optimization is the genetic algorithm (GA) developed from evolutionary theory (GA) (Goldberg and Samtani 1986). Guimarães et al. (2022) in the optimal design of concrete-filled composite columns; Rao and Babu (2006) in the cost optimization design of short columns by combining with artificial neural network method; Pierott et al. (2021), Yousif and Najem (2013), Deliktaş et al. (2009), and Govindaraj and Ramasamy (2005) in the cost design of reinforced concrete simply supported and continuous beams; Alqedra et al. (2011) in the design of reinforced concrete prestressed beams; Sahab et al. (2005) and Nimtawat and Nanakorn (2010) in the design of slabs; Shooli et al. (2019) and Mergos (2021) in the optimal cost design of reinforced concrete frames; Dos Santos et al. (2023) analyzed the cost and CO_2 emission of reinforced concrete beams with the help of genetic algorithm. The Jaya algorithm, which is also used in this study, has not been studied in the field of civil engineering. Öztürk et al. (2020) used Jaya algorithm for cost and design optimization on retaining walls and Yücel et al. (2023) used Jaya algorithm to minimize the weight of steel truss systems of different sizes. Kaveh and Hamedani (2023) compared the results of certain examples from the literature against the hybrid set-theoretical Jaya algorithm (ST-JA) classic Jaya algorithm and other metaheuristic algorithms because of classic Jaya algorithm's likelihood of early convergence and getting stranded in the local optimum under certain circumstances. They revealed that convergence speed and results performed better based on numerical results when compared to ST-JA classic Jaya algorithm and other metaheuristic algorithms. Pham and Nguyen (2024) took advantage of a Jaya-based optimization algorithm demonstrated to be innovative for the analysis of fuzzy displacements of two-dimensional and 3D cage beams under static loads. Du et al. (2018) conducted a study intended to determine sites of damage at structures and their scope, using Jaya algorithm. Çakıroğlu et al. (2023b) used Jaya algorithm and Manta Ray Foraging Optimization in order to ascertain optimal cross-section dimensions of steel pipe columns with concrete filling and minimize CO_2. Dede (2018) used Jaya algorithm to conduct analysis and optimal design of design and steel grillage structures and concluded that Jaya algorithm was effective in the analysis of steel grillage structures.

In this study, the Jaya algorithm developed by Rao (2016) is used for the optimum design of reinforced concrete beam sections under the effect of shear force, moment force and torsional force. Different torsional moment effects are considered to see the effect of the torsional moment on the reinforced concrete beam section. As part of this study, 5 different torsional moment sizes were used for 10 different beam designs. For the purpose of design of reinforced concrete cross-section, design restrictions and building rules specified in ACI 318 (Building Code Requirements for Structural Concrete) regulation were taken into account and two different concrete classes; i.e. C30 and C35, were used for the design of beam cross-sections.

2. Methodology

Jaya algorithm is a population-based algorithm composed of a single part and it is an algorithm that is easier to use when compared to algorithms made of 2 phases such as teaching- and learning-based optimization algorithms used prevalently in the field of civil engineering, flower pollination algorithm, harmony search algorithm, genetic algorithm and differential evolution algorithm. In Jaya algorithm, design variables are randomly assigned and the algorithm works on the principle of moving away from the worst solution and converging to the best solution. The algorithm determines, at the first phase, the best and the worst values at the population, and each new solution is updated so that it remains between the best and the worst solutions, then the updated solution is evaluated based on updated design restrictions, the best solution is chosen. The process continues via iterations. The process is terminated when it reaches a certain number of iterations or appropriate values. The equation of the one-part algorithm is shown in Eq. (1) below.

$$x_i^{j,t+1}= x_i^{j,t} + r_1(x_i^{*}- |x_i^{j,t}|) - r_2 (x_i^{w}-| x_i^{j,t}|)$$
$$i=1, 2, \ldots,n \; ; j=1, 2, \ldots,p \; ; t=1, 2, \ldots,t_{\max} \qquad (1)$$

In Eq. (1), (x_i^*) is the best available solution and (x_i^w) is the worst available solution. In the formula, r_1 and r_2 are random numbers between 0 and 1. r_1 (x_i^*- $|x_i^{j,t}|$) portion of the equation ensures that the solution converges to the best result whereas the term r_2 (x_i^w-$|x_i^{j,t}|$) makes sure that the solution gets away from the worst result. Real numbers r_1 and r_2, randomly created in the equation, ensure that design space is more effectively inspected while absolute value $|x_i^{j,t}|$ further increases the search capability of the algorithm. The Jaya algorithm compares its results with each other in the current solution and continues by updating itself to find the better solution in the next solution. This process continues until the stopping criterion is met. The stopping criterion is usually constrained by a result threshold or number of iterations. The flowchart about Jaya algorithm is given in Fig. 1.

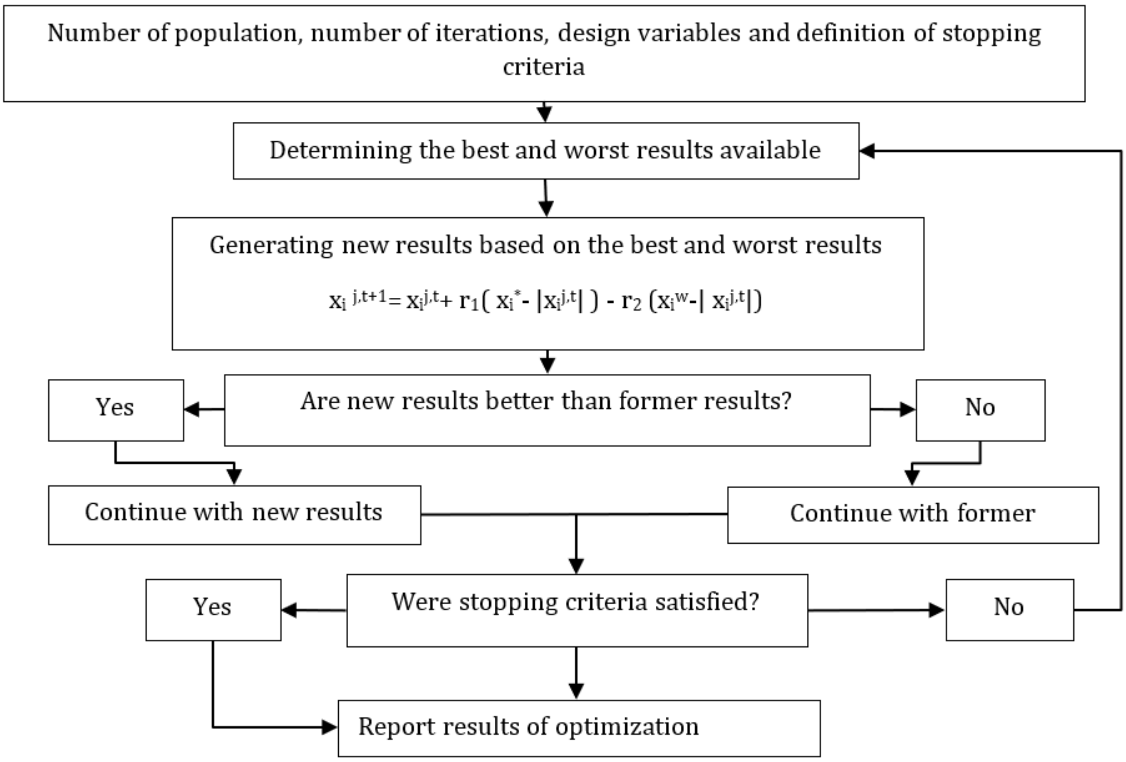

Fig. 1. Flow chart of the optimization method.

One of the basic requirements of engineering optimization algorithms is to clearly define the problem. This process involves the identification of the problem data, design variables, definition of the design constraints and the determination of the parameters of the algorithm. The design constants and design variables are shown in Table 1. In reinforced concrete beam optimization, the design variables are width (b_w), height (h), area of longitudinal reinforcement, size of shear reinforcement and spacing of shear reinforcement. A cross-section of the beam design is shown in Fig. 2.

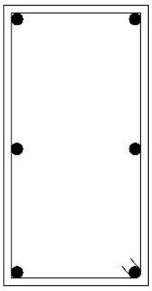

Fig. 2. Details of beam cross-section and reinforcement.

Table 1. Design variables and design constants.

Explanation	Symbol	Unit	Value
Beam width	h	mm	250–400
Beam depth	b	mm	350–600
Compressive strength of concrete	f_{ck}	MPa	30–35
Yield strength of steel	f_{yk}	MPa	420
Modulus of elasticity	E	MPa	27800
Specific density of concrete	γ_c	t/m^3	2.5
Specific density of steel	γ_s	t/m^3	7.86
Concrete cover	d'	mm	40
Stirrup	Ø	mm	8–14

Since ACI 318 is used as a reference for reinforced concrete design in international projects and many countries have adopted ACI 318 directly, this study considers ACI 318 (Building code requirements for structural concrete and commentary) for design constraints and construction rules.

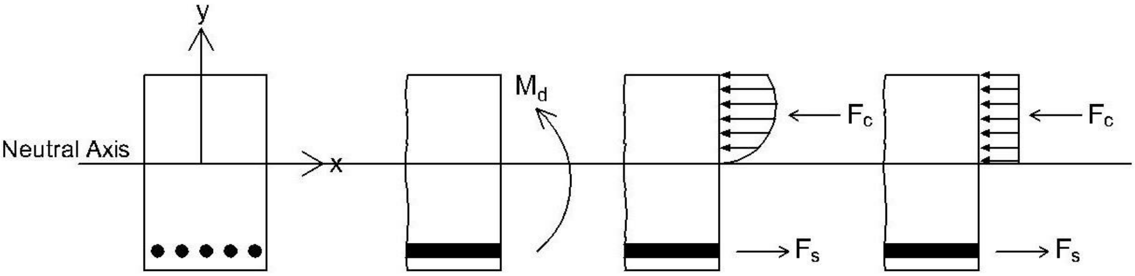

Fig. 3. Assumption of the equivalent load distribution.

As shown in Fig. 3, the resultant force forming in the concrete pressure region in the upper part of the neutral axis is called F_c whereas the resultant force forming in the tensile region in the lower part of the neutral axis is called F_s.

$$F_c = 0.85 \cdot f'_c \cdot b \cdot a \tag{2}$$

In Eq. (2), concrete compressive strength was multiplied by 0.85 and a indicates equivalent pressure block depth.

$$a = \beta_1 \cdot \mathrm{c} \tag{3}$$

where c is the depth of the neutral axis in the pressure region. At ACI 318, β_1 represents a rectangular pressure block, which is shown in Eq. (4).

$$\beta_1 = 0.85 \quad 17\ \mathrm{MPa} < f'_c < 28\ \mathrm{MPa}$$

$$\beta_1 = 0.85 - 0.0071428\,(f'_c - 28) \quad f'_c > 28\ \mathrm{MPa} \tag{4}$$

The resultant tensile force occurring in the tensile region is shown in Eq. (5).

$$F_s = A_s \cdot f_y \tag{5}$$

where A_s means the reinforcement region. A balanced breakage occurs when concrete unit shortening (ε_c) reaches concrete ultimate unit shortening (ε_c=0.003), and unit shortening of tensile reinforcement (ε_y) reaches the yield strength of the reinforcement at the same time. According to ACI 318, breakage in beams must be designed according to sub-equilibrium breakage. Calculations for sub-equilibrium breakage are calculated according to the balanced reinforcement ratio.

Balanced reinforcement ratio ρ_b is calculated with the following equation based on form changing status shown in Fig. 4 with known material characteristics and dimensions.

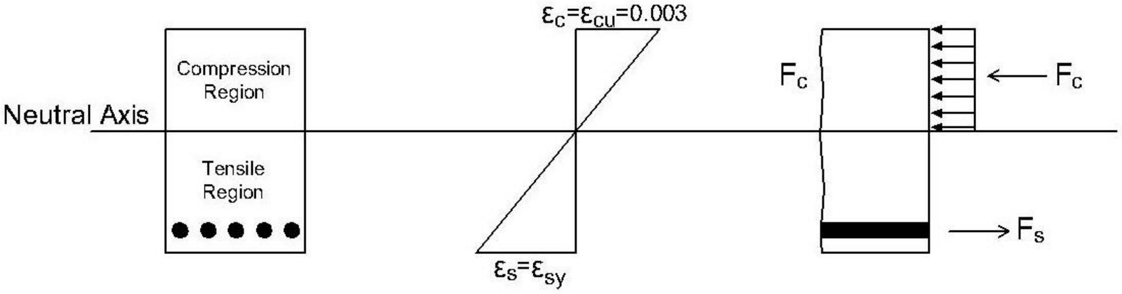

Fig. 4. Internal forced forming in the beam cross-section.

$$\rho_b = 0.85 \cdot \beta_1 \frac{f'_c}{f_y}\left(\frac{600}{600+f_y}\right) \tag{6}$$

The maximum reinforcement ratio ($\rho_{\max}$) must not be higher than 0.75 times the balanced reinforcement and the maximum reinforcement ratio ($\rho_{\max}$) must be lower than the value 0.025 for beams to demonstrate ductile behavior.

In ACI 318, the minimum longitudinal reinforcement ratio of beams is calculated as shown in Eqs. (7) and (8).

$$A_{s,\min} \geq \frac{\sqrt{f'_c}}{4f_y}\, b \cdot d \tag{7}$$

$$A_{s,\min} \geq \frac{1.4}{f_y}\, b \cdot d \tag{8}$$

If reinforcement ratios so calculated are lower than the minimum conditions specified in Eqs. (7) and (8), the ratio of minimum longitudinal reinforcement will be taken into account. If the longitudinal reinforcement ratio proves to be higher than the maximum reinforcement ratio, the dimensions of the cross-section are changed and calculations are repeated. Once reinforcements about the beam are calculated, the stirrup design is done. Rules and restrictions of required regulation for the design of stirrup should satisfy the following requirements;

Shearing strength provided by concrete;

$$V_c = 0.17\sqrt{f'_c}\, b \cdot d \tag{9}$$

Shearing strength provided by reinforcement;

$$V_s = 0.67\sqrt{f'_c}\, b \cdot d \tag{10}$$

Minimum shearing reinforcement region;

$$A_{v,\min} = 0.35\ \frac{b_w s}{f_{yt}} \tag{11}$$

where s refers to the distance between stirrup reinforcements. Distance between shearing reinforcements;

$$s \leq \begin{cases} d/4 \\ 8\phi_{min} \\ 150 \text{ mm} \end{cases} \tag{12}$$

The existence of a torsional moment in a structure system is a mandatory condition, this is called conformity torsion and hyperstatic systems generally have conformity torsion. Torsional moment load to shearing tensions and shearing reinforcements are used at elements to meet such tensions. According to ACI 318, if shearing force and conformity torsional have an impact at the same time, rules and restrictions introduced by the regulation are shown in the equations below.

Dimension check of the required cross-section is carried out according to Eqs. (13) and (14) to be able to keep diagonal cracks driven by torsional moment under control.

$$\frac{T}{S} + \frac{V}{b_w d} \leq 0.22\, f_{cd} \tag{13}$$

$$\sqrt{\left(\frac{V}{b_w d}\right)^2 + \left(\frac{T p_h}{1.7 A_{oh}^2}\right)^2} \leq \emptyset\left(\frac{V_c}{b_w d} + 0.66\sqrt{f'_c}\right) \tag{14}$$

In Eq. (14), T means torsional moment, p_h perimeter of cross-section remaining between reinforcements whereas A_{oh} means the area remaining between corner reinforcements, V_c means shearing force and $\emptyset$ means reduction coefficient.

Calculation of torsion stirrup;

$$A_t = \frac{T\,s}{2\emptyset A_o f_{yt} cot\theta} \tag{15}$$

Calculation of shearing reinforcement;

$$A_v = \frac{V\,s}{f_{yt} d} \tag{16}$$

The value calculated for the torsion stirrup in Eq. (15) is for one arm of the stirrup whereas the value calculated in Eq. (16) is for two arms of the stirrup. The total area of the stirrup area is shown in Eq. (17).

$$A_{v+t} = A_v + 2A_t \tag{17}$$

Distance between stirrups for elements under the effect of both torsional effect and shearing effect should not exceed conditions specified in Eq. (18).

$$s \leq \begin{cases} d/2 \\ {}^{ue}/_{8} \\ 300 \text{ mm} \end{cases} \quad (18)$$

The total area of closed stirrup arms for elements under the effect of both the torsional effect and shearing effect is shown in Eq. (19).

$$A_v + 2A_t = 0.062 \sqrt{f'_c} \frac{b_w s}{f_{yt}} \geq 0.35 \frac{b_w s}{f_{yt}} \quad (19)$$

The minimum longitudinal reinforcement area for the torsional moment is shown in Eq. (20).

$$A_l = \frac{A_t}{s} p_h \frac{f_{yt}}{f_y} cot^2\theta \quad (20)$$

3. Numerical Example

In this study, the sizing and reinforcement of 10 different reinforced concrete beam sections were optimized. The external loads consist of shear force, bending moment and torsional moment as shown in Fig. 5. Different torsional moments are applied on the section and the effect of torsional moment on the beam section size and reinforcement is investigated.

The shear force and bending moment acting on the section are taken as 100 kN and 100 kNm, respectively. The torsional moment was taken as 10, 20, 30, 40, and 50 kNm. The external loads acting on the beam section and the concrete classes used in the beam section are shown in Table 2. Table 2 shows 10 different beam cross-sections. 100 kN bending moment of shearing force having an impact upon the beam cross-section was selected as 100 kNm and remained stable at all samples, torsional moment and concrete classes were changed and their impact upon the concrete cross-section was examined. In Table 2, *B* shows that the cross-section is a beam and the numerical value shows the torsional moment having an impact upon the beam whereas *L* shows the concrete compressive strength is 30 MPa and *H* shows concrete compressive strength is 35 MPa.

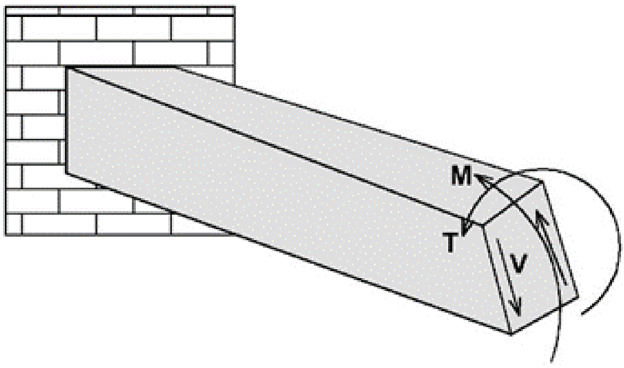

Fig. 5. Loads acting on the beam section.

Table 2. Sectional effects and concrete classes.

Sample number	Shear force (*kN*)	Bending moment (*kNm*)	Torsional moment (*kNm*)	Concrete class
B10L	100	100	10	C30
B10H	100	100	10	C35
B20L	100	100	20	C30
B20H	100	100	20	C35
B30L	100	100	30	C30
B30H	100	100	30	C35
B40L	100	100	40	C30
B40H	100	100	40	C35
B50L	100	100	50	C30
B50H	100	100	50	C35

Conducting an optimization study by adding a torsional moment of differing sizes to a beam cross-section was tried for the first time with this study and 10 different beam cross-sections were designed according to ACI 318 regulation, using Jaya algorithm. In addition to different torsional moments, 2 different concrete classes were used in the beam cross-section. In respect of sample numbering in Table 2, *B* indicates that the element is a beam, numbers at the middle part indicate the torsional moment having an impact upon beam cross-section, cross-section *L* indicates that the class of concrete used is C30, and *H* indicates that the class of concrete used in the cross-section is C35. Table 3 shows varying torsional moment and bending reinforcement area of samples of beam designed according to concrete classes, body reinforcement area, diameter and range of stirrup and dimensions of beam cross-section.

A total of 10 beam sections are studied in the study and the optimum results are given in Table 3.

4. Conclusions

Unlike existing studies from the literature, the effect of torsional moment was examined in this study. The optimum values of reinforced concrete beam sections are analyzed with the help of Jaya algorithm. The effect of torsional moment is seen by examining the optimum beam section results. As the torsional moment increases, the cross section and body reinforcement of the beam increases and the stirrup spacing decreases. In the first phase, the algorithm increases the cross-section area since the unit cost of the concrete is lower than the unit cost of the reinforcement. In a case satisfying minimum material cost, the algorithm increases cross-section height (h), from among dimensions of cross-section, at beams whereas cross-section width (b_w) makes sure that it remains at minimum limit, where possible. An increase in torsional moment increases the area of longitudinal reinforcement at the beam cross-section and reduces the ranges of stirrups. The Jaya algorithm used in the study is found to be effective in finding the optimum values of the beam cross-section. Jaya algorithm is a suitable algorithm for solving optimization problems of reinforced concrete elements. It is considered to be usable for other reinforced concrete elements or systems. The ability to design reinforced concrete elements under many load combinations in a very short time through optimization algorithms will save a great deal of time for engineers. Structures built using optimum cross-sections will enable us to use our world's limited resources more efficiently.

Table 3. Optimization results.

Sample number	Concrete class	Torsional moment (kNm)	Flexural reinforcement (mm^2)	Web reinforcement (mm^2)	Stirrup (d/s)	Section (b_w/h) (mm)
B10L	C30	10 kNm	538.35	308.62	Ø8/147.5	250/500
B10H	C35	10 kNm	535.18	308.62	Ø8/147.5	250/500
B20L	C30	20 kNm	481.85	598.32	Ø8/99.1	250/550
B20H	C35	20 kNm	479.59	598.32	Ø8/103.6	250/550
B30L	C30	30 kNm	481.85	897.48	Ø8/67.9	250/550
B30H	C35	30 kNm	479.59	897.48	Ø8/69.9	250/550
B40L	C30	40 kNm	534.66	1034.75	Ø8/60.7	300/500
B40H	C35	40 kNm	532.08	1034.75	Ø8/62.7	300/500
B50L	C30	50 kNm	534.66	1293.40	Ø8/50.0	300/500
B50H	C35	50 kNm	532.08	1293.40	Ø8/50.1	300/500

Acknowledgements

None declared.

Funding

The authors received no financial support for the research, authorship, and/or publication of this manuscript.

Conflict of Interest

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

Author Contributions

All of the authors made substantial contributions to conception and design, or acquisition of data, or analysis and interpretation of data; were involved in drafting the manuscript or revising it critically for important intellectual content; and gave final approval of the version to be published.

Data Availability

The datasets created and/or analyzed during the current study are not publicly available, but are available from the corresponding author upon reasonable request.

REFERENCES

ACI 318-05 (2008). Building code requirements for structural concrete (ACI 318-05) and commentary. ACI Committee, American Concrete Institute, USA.

Alqedra M, Arafa M, İsmail M (2011). Optimum cost of prestressed and reinforced concrete beams using genetic algorithms, *Journal of Artificial Intelligence*, 4(1), 76-88.

Bekdaş G, Çakıroğlu C, İslam K, Kim S, Geem ZW (2022a). Optimum design of cylindrical walls using ensemble learning methods. *Applied Sciences*, 12, 2165.

Bekdaş G, Çakıroğlu C, Kim S, Geem ZW (2022b). Optimization and predictive modeling of reinforced concrete circular columns. *Materials*, 15, 6624.

Bekdaş G, Niğdeli SM (2016). Optimum design of reinforced concrete columns employing teaching-learning based optimization. *Challenge Journal of Structural Mechanics,* 2(4), 216-219.

Bekdaş G, Temür R (2017). Metaheuristic approaches for optimum design of cantilever reinforced concrete retaining walls. *Challenge Journal of Structural Mechanics*, 3(1), 23-30.

Çakıroğlu C, Bekdaş G, Kim S, Geem ZW (2020a). Optimisation of shear and lateral–torsional buckling of steel plate girders using metaheuristic algorithms. *Applied Sciences*, 10, 3639.

Çakıroğlu C, Bekdaş G, Geem ZW (2020b). Harmony search optimisation of dispersed laminated composite plates. *Materials*, 13, 2862.

Çakıroğlu C, İslam K, Bekdaş G, Kim S, Geem ZW (2021a). Metaheuristic optimization of laminated composite plates with cut-outs. *Coatings*, 11, 1235.

Çakıroğlu C, İslam K, Bekdaş G, Kim S, Geem ZW (2021b). CO_2 emission optimization of concrete-filled steel tubular rectangular stub columns using metaheuristic algorithms. *Sustainability*, 13, 10981.

Çakıroğlu C, İslam K, Bekdaş G, Nehdi ML (2023a). Data-driven ensemble learning approach for optimal design of cantilever soldier pile retaining walls. *Structures*, 51, 1268-1280.

Çakıroğlu C, İslam K, Bekdaş G (2023b). Manta Ray Foraging and Jaya Hybrid Optimization of concrete filled steel tubular stub columns based on CO_2 emission. *Hybrid Metaheuristics in Structural Engineering*, 480, 111-125.

Dede T (2018). Jaya algorithm to solve single objective size optimization problem for steel grillage structures. *Steel and Composite Structures*, 26(2), 163-170.

Dede T, Ayvaz Y (2015). Combined size and shape optimization of structures with a new meta-heuristic algorithm. *Applied Soft Computing*, 28, 250-258.

Deliktaş B, Bikçe M, Coşkun H, Türker HT (2009). Betonarme kirişlerin optimum tasarımında genetik algoritma parametrelerinin etkisinin belirlenmesi. *Fırat University Journal of Engineering Science*, 21(2), 125-132. (in Turkish)

Dos Santos NR, Alves EC, Kripka M (2023). Towards sustainable reinforced concrete beams: multi-objective optimization for cost, CO_2 emission, and crack prevention. *Asian Journal of Civil Engineering*, 25, 575-582.

Du DC, Vinh HH, Trung VD, Quyen NTH, Trung NT (2018). Efficiency of Jaya algorithm for solving the optimization-based structural damage identification problem based on a hybrid objective function. *Engineering Optimization*, 50(8), 1233-1251.

El-Sayed TA (2019). Flexural behavior of RC beams containing recycled industrial wastes as steel fibers. *Construction and Building Materials*, 212, 27-38.

El-Sayed TA, Shahen YBI (2020). Flexural performance of recycled wheat straw ash-based geopolymer RC beams and containing recycled steel fiber. *Structures*, 28, 1713-1728.

Ghali MKN, El-Sayed TA, Salah A, Khater N (2024). Performance of RC beams under shear loads strengthened with metallic and non-metallic fibers. *Buildings*, 14, 1869.

Goldberg DE, Samtani MP (1986). Engineering optimization via genetic algorithm. *Proceedings of Ninth Conference on Electronic Computation,* ASCE, New York, United States of America, 471-482.

Govindaraj V, Ramasamy JV (2005). Optimum detailed design of reinforced concrete continuous beams using Genetic Algorithms. *Computers & Structures*, 84(1-2), 34-48.

Guimarães SA, Klein D, Calenzani AFG, Alves EC (2022). Optimum design of steel columns filled with concrete via genetic algorithm: environmental impact and cost analysis. *International Engineering Journal*, 75(2), 117-128.

Jahjouh MM, Arafa MH, Alqedra MA (2013). Artificial Bee Colony (ABC) algorithm in the design optimization of RC continuous beams. *Structural and Multidisciplinary Optimization*, 47, 963-979.

Kaveh A, Hamedani KB (2023). Discrete structural optimization with set-theoretical Jaya algorithm. *Iranian Journal of Science and Technology, Transactions of Civil Engineering*, 47, 79-103.

Kayabekir AC, Yücel M, Bekdaş G, Nigdeli SM (2020). Comparative study of optimum cost design of reinforced concrete retaining wall via metaheuristics. *Challenge Journal of Concrete Research Letters*, 11(3), 75-81.

Nigdeli SM, Bekdaş G, Yang X-S (2018). Metaheuristic optimization of reinforced concrete footings. *KSCE Journal of Civil Engineering*, 22, 4555-4563.

Nimtawat A, Nanakorn P (2010). A genetic algorithm for beam–slab layout design of rectilinear floors. *Engineering Structures*, 32(11), 3488-3500.

Özturk HT, Durmus A (2013). Optimum cost design of RC columns using artificial bee colony algorithm. *Structural Engineering and Mechanics*, 45(5), 643-654.

Öztürk HT, Dede T, Türker E (2020). Optimum design of reinforced concrete counterfort retaining walls using TLBO, Jaya algorithm. *Structures*, 25, 285-296.

Pham HA, Nguyen B D (2024). Fuzzy structural analysis using ımproved Jaya-based optimization approach. *Periodica Polytechnica Civil Engineering*, 68(1), 1-7.

Pierott R, Hammad AWA, Haddad A, Garcia S, Falcon G (2021). A mathematical optimisation model for the design and detailing of reinforced concrete beams. *Engineering Structures*, 245, 112861.

Rao HS, Babu BR (2006) Optimized column design using genetic algorithm based neural networks. *Indian Journal of Engineering and Materials Sciences*, 13 (6), 503-511.

Rao RV, Savsani VJ, Vakharia DP (2011). Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems, *Computer-Aided Design*, 43(3), 303-315.

Rao RV (2016). Jaya: A simple and new optimization algorithm for solving constrained and unconstrained optimization problems. *International Journal of Industrial Engineering Computations*, 7(1), 19-34.

Sahab MG, Ashour AF, Toropov VV (2005). A hybrid genetic algorithm for reinforced concrete flat slab buildings. *Computers & Structures*, 83(8-9), 551-559.

Shooli AR, Vosoughi AR, Banan MR (2019). A mixed GA-PSO-based approach for performance-based design optimization of 2D reinforced concrete special moment-resisting frames. *Applied Soft Computing Journal*, 85, 105843.

Sönmez M (2011). Artificial Bee Colony algorithm for optimization of truss structures. *Applied Soft Computing*, 11(2), 2406-2418.

Tapao A, Cheerarot R (2017). Optimal parameters and performance of artificial bee colony algorithm for minimum cost design of reinforced concrete frames. *Engineering Structures*, 151, 802-820.

Temur R, Bekdaş G (2016). Teaching learning-based optimization for design of cantilever retaining walls. *Structural Engineering and Mechanics*, 57(4), 763-783.

Yousif ST, Najem RN (2013). Optimum cost design of reinforced concrete continuous beams using Genetic Algorithms. *International Journal of Applied Sciences and Engineering Research*, 2(1), 79-92.

Yücel M, Niğdeli SM, Bekdaş G (2023). Optimization of truss structures by using a hybrid population-based metaheuristic algorithm. *Arabian Journal for Science and Engineering*, 49, 5011-5026.