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Research Article

Optimization of reinforced concrete beam using hybrid algorithms with multi-objective function as CO_2 emission and cost

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ABSTRACT

In this study, algorithms with two objective functions are defined considering the TS500 (2000) (Reinforced concrete structures design and construction rules) and TBDY (2018) (Turkey Building Earthquake Regulation) standards for rectangular beam design. These objective functions were determined as CO_2 emission and cost. Optimizations were performed in MATLAB program using the Hybrid Algorithm of Teaching-Learning Based Optimization and Jaya Algorithm. In the case of using two objective functions, cases were created by multiplying the coefficient values found in the objective function according to the formula with the cost and CO_2 emission values at different rates in order to prevent CO_2 emission which is one of the biggest problems for the world. In the objective function, each rate used for CO_2 and cost is implemented in a manner that increases or diminishes the impact of these values. In this way, comparisons were made between the cross-section dimensions to be formed according to not only impact rates but also the reinforcement area to be used, the CO_2 emission and cost values that will arise as a result of these. Impact rates are related to cost and CO_2 rate in the objective function, and the total rate is chosen as 1. Impact rates for cost are chosen as 0.1, 0.3 along with 0.5, and comparisons between the results are checked. In addition, recyclable and non-recyclable steel with different properties were used in separate analyses and the values were compared. Since the CO_2 rate released by the non-recyclable steel is very high compared to the recyclable steel, the results show that the CO_2 emission value is higher and this causes the objective function value to increase.

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1. Introduction

Most of the engineering works that have been done and completed in the past are designed by taking into account the conditions such as strength and service life. However, in addition to strength and other required properties, sustainability studies have begun to be considered an important design condition for the protection of nature. One of the biggest reasons for the adoption of sustainable designs is the increase in the amount of annual CO_2 emissions. While the annual CO_2 emission was around 6 billion tons worldwide before the 1950s, today this value is measured as more than 38 billion tons (URL-1 2023) by increasing rapidly. Therefore, the CO_2 emission reduction process is carried out by different studies in different engineering fields.

When the construction sector and the buildings are taken into account, it is explained in the reports that according to the data explained above, approximately 38% of the CO_2 rate is released worldwide. Moreover, that 5% CO_2 is released by cement is computed by IPCC 2006 standard (Kara et al. 2018). For this reason, significant studies are carried out in terms of both reducing CO_2 emissions and reducing costs to realize the most appropriate and efficient design in the construction industry. These studies can be done in different ways. To exemplify, these are the use of materials that are less harmful to the environment and have high durability by increas-

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ing the variety of materials that can be used (Kayabekir et al. 2020; Li 2011; Habert and Roussel 2009), the availability of sufficient cross-section dimensions according to the force affecting the necessary construction element and the standard of the country where it is located, the selection of more effective structural systems and the recyclability of the materials used in the construction. As result of such studies, it contributes to the prevention of global climate change, reducing the carbon footprint of buildings, efficient use of resources and increasing efficiency in the project process. In order to control such as emissions and cost, metaheuristic algorithms have been used in many areas to reach pertinent design, and the objective function of a design may contain more than one variable. Cakiroglu et al. (2021a) have conducted to find CO_2 and cost optimization for concrete-filled steel tubular columns. In addition, Cakiroglu et al. have used Harmony Search (HS) (2021b) and Manta Ray Foraging – Jaya Hybrid Optimization (2023a) to accomplish CO_2 emission for concrete-filled steel tubular rectangular stub columns. Cantilever shoulder pile retaining walls which are indispensable to remain steady in the soil have reached optimal design by using a method of data-driven ensemble learning (2023b). Cakiroglu and Bekdaş (2022) have analysed CFST stub columns to find the axial load capacity. In order to display the algorithms how many iterations they could reach the objective function in problem as optimization cost, Çoşut et al. (2023) have utilized the algorithms which are Harmony Search (HS), Differential Evolution Algorithm (DE), Hybrid Algorithm, Flower Pollination Algorithm (FPA), Jaya Algorithm, Teaching- Learning Based Optimization (TLBO). Temür (2021) has generated a Hybrid TLBO algorithm for the optimum design of cantilever retaining walls under seismic loads. The type of optimization can be different and one of them known as multi-objective optimization has been used many times in the optimization of beams. Aydoğdu (2017) has performed multi-objective optimization of cantilever retaining walls in terms of cost and CO_2. Paya- Zaforteza et al. (2009) have optimized reinforced concrete frames by using simulated annealing and Spanish Code as multi-objective functions related to CO_2 emission and cost. Leps and Sejnoha (2003) have used genetic algorithms to reach the optimum total cost for steel-reinforced concrete structures. Camp and Assadollahi (2013) used a hybrid algorithm which was a big bang-big crunch algorithm about optimizing CO_2 and cost in the design of reinforced concrete footings. Kripka and de Medeiros (2012) studied the cross-sectional optimization of reinforced concrete columns at the firstly cost, after that, they utilized Life Cycle assessment to reach the environmental effect. Therefore, they have tried to decrease the amount of CO_2 according to cost [10]. Reinforced concrete structures which were beams have been optimized by Afshari et al. (2019), and also, they have focused on the approaches of multi-objective optimization. Yeo et al. (2015) studied to generate a design which was about reinforced concrete structures to minimize CO_2 emission. Joyner et al. (2021) have optimized the buildings according to resilience-based seismic design, and life span performance along with conditional performance have been controlled. Yücel et al. (2021) have optimized rectangular beams in terms of CO_2 emission to design an environmentally friendly structure element; however, Abubakar et al. (2021) have used genetic algorithms to optimize the design of rectangular beams. Also, machine learning techniques are a new trend in the prediction of optimum design parameters without rerunning the iterative optimization process (Ocak et al. 2013, Aydın et al. 2013).

In this study, the optimization of the rectangular reinforced concrete beam in terms of both CO_2 emission and cost was carried out with the hybrid algorithm created by the synthesis of metaheuristic algorithms using the MATLAB program. Since two objective functions were defined in the optimization process, their sum was adjusted in certain proportions, the dimensions of the rectangular beam, the required reinforcement area, the cost and the released CO_2 values were recorded and the results were compared according to the determined rate values. In addition, the differences in the variable and objective function that occur when steels with different properties are used were compared.

2. Features and Design of the Beam

Many countries have developed their own building design and construction regulations over time. These standards have evolved and developed based on a certain accumulation of knowledge, laboratory studies, and experience with destructive natural disasters. As a result, designs for resilient systems can be developed against unwanted and destructive situations.

In structural design, beams are widely used as building elements. These elements not only perform well against bending moments and shear forces but also transfer loads from slabs to columns. Beams can be designed in various shapes, such as T-shaped, I-shaped, and L-shaped. Depending on the desired design, there may be some minor changes in the calculation formulas. Additionally, the span length can vary depending on the desired design, while keeping within certain limits (Doğangün 2019).

In this study, the design of a rectangular beam (Fig. 1) is carried out by considering the TS 500 (2000) and TBDY (2018) regulations, and the necessary equations for the design are presented.

In the following equations, f_{ctd} is the tensile strength of concrete, f_{ck} is the characteristic strength of concrete, f_{cd} is the design strength of concrete, f_{yk} is the characteristic yield strength of steel, f_{yd} is the design yield strength of steel. The depth of the compression block (Eq. 2) is calculated based on the effective height of the beam (d), the load affecting the beam, the span, and the concrete grade used. As a consequence, the reinforcement area can be found in Eq. (3).

$$f_{ctd} = 0.35 \times \frac{\sqrt{f_{ck}}}{1.50}, \quad f_{cd} = \frac{f_{ck}}{1.50}, \quad f_{yd} = \frac{f_{yk}}{1.15} \tag{1}$$

$$a = d \pm \sqrt{d^2 - \frac{2 \times M_d}{0.85 \times f_{cd} \times b}} \tag{2}$$

$$A_s = \frac{M_d}{f_{yd} \times \left(d - \frac{a}{2}\right)} \tag{3}$$

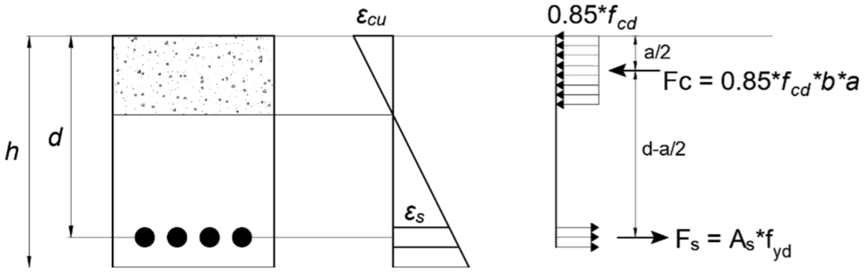

Fig. 1. Under loading for RC beam.

The adequacy of a beam in resisting shear forces under loading conditions is examined, and accordingly, the required reinforcement area is selected and placed at the necessary distance in compliance with regulations. The shear force value provided by concrete is given in Eq. (4).

$$V_{cr} = 0.8 \times \frac{0.65 \times f_{ctd} \times b \times d}{1000} \tag{4}$$

In certain situations and under specific loads, even if it is calculated that all shear forces of the designed beam are carried by the concrete (V_{cr}), reinforcement calculation and placement should be done according to the minimum requirements of the regulations. This will ensure that the structural element functions effectively under dynamic loads, preventing damage to the system. V changing by loading (Q) is the shear force of system.

$$V_d = V - \frac{Q \times \left(d + \frac{a}{2}\right)}{1000} \tag{5}$$

The stirrups used to resist shear forces are placed at different distances in the wrapping and middle regions (Fig. 2). This is because the beam will be subjected to maximum shear forces at the column-beam joints, and a denser and closer stirrup arrangement is required for the safe transfer of these forces. According to the regulations, the distances between the stirrups to be placed in these two regions are given in Eqs. (6) and (7).

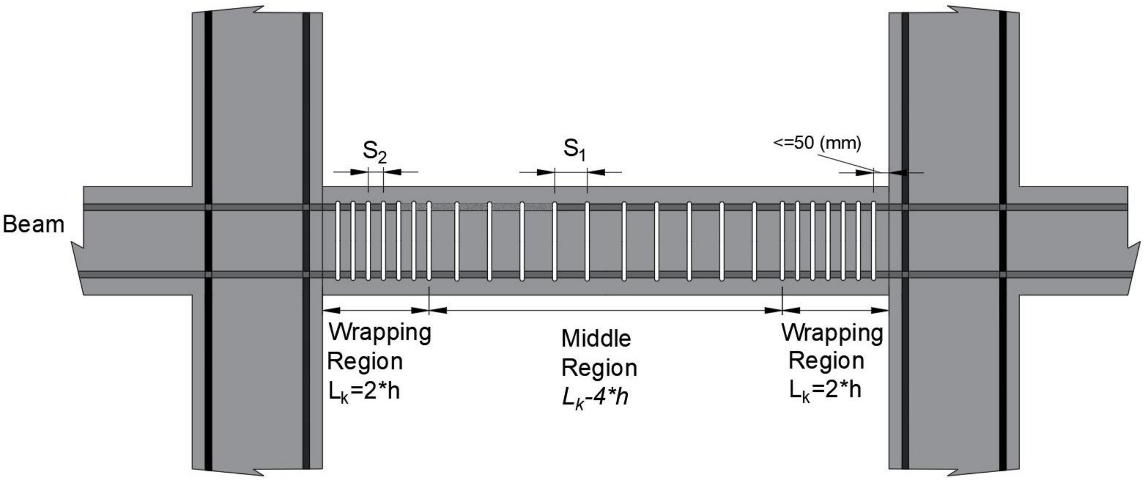

Fig. 2. Layout of the stirrups.

$$\text{middle region} \leq \begin{cases} V_d \leq 3 \times V_{cr} & S_1 = \frac{d}{2} \\ V_d > 3 \times V_{cr} & S_1 = \frac{d}{4} \\ S_1 > 350 \text{ mm} & S_1 = 350 \text{ mm} \end{cases} \tag{6}$$

$$\text{wrapping region } (S_2) \leq \begin{cases} \frac{h}{2} \\ 8 \times \emptyset \ (\emptyset 8 \text{ or } \emptyset 10) \\ 150 \text{ mm} \end{cases} \tag{7}$$

For the concrete to be placed homogeneously between the reinforcements, the horizontal and vertical net distances between the longitudinal reinforcements must be at a certain value. These values are determined by considering the maximum aggregate diameter, which is 22 mm (D), that can be used in the concrete, constant and rebar diameter (Eq. (8)).

$$\text{net distance} \geq \begin{cases} 25 \\ \emptyset \ (\emptyset \geq \emptyset 12) \\ 4 \times \frac{D}{3} \end{cases} \tag{8}$$

3. Metaheuristic Algorithm

The metaheuristic algorithms which are a comprehensive problem-solving method for a variety of problems have been found and developed over time by inspiring natural events (Bekdaş et al. 2021). Flower Pollination Algorithms (FPA) (Yang 2012), Jaya Algorithm (Rao 2016), Teaching-Learning Based Optimization (TLBO) (Rao 2011) and Bat Algorithm (Yang and Gandomi 2014) can be given as examples. These algorithms which are more effective to reach objective functions than traditional methods can be used for finding optimal solutions. Furthermore, various fields employ the algorithms such as engineering, manufacturing, financial risk management, artificial intelligence, machine learning, operation research and management science. All these fields have some goals such as optimizing CO_2 emission, cost along with weight. Thus, engineers should apply the objective function according to the priority of the problem. Objective functions can be generated as single-objective functions, multi-objective functions as well as constraint optimization functions.

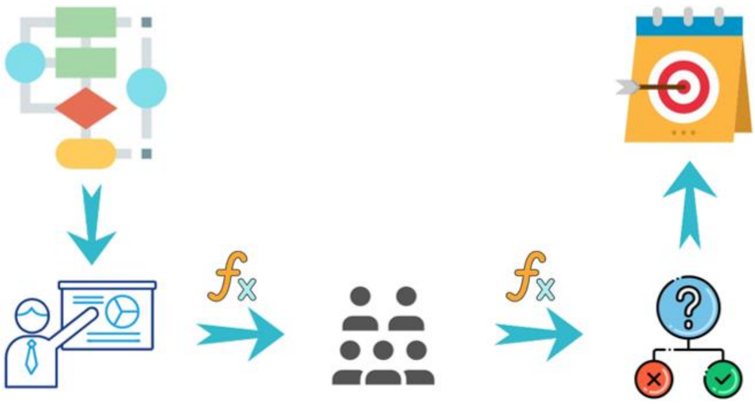

Fig. 3. The metaheuristic algorithm process.

3.1. Hybrid algorithm

Nowadays, there are several metaheuristic algorithms which have different properties like phase number, equations and control parameters. In addition, hybrid algorithms have been developed over time to facilitate the efficient and effective resolution of more complex and comprehensive problems. These algorithms are obtained by combining two or more algorithms, thereby improving optimization performance. The ways to combine metaheuristic algorithms (Khajehzadeh 2016) are sequential hybridization, parallel hybridization and integrative hybridization. In addition, some hybrid algorithms have been combined as TLBO-Jaya (Teaching-Learning Based Optimization- Jaya Algorithm), GAAP (Hybrid Ant Colony-Genetic Algorithm), ACO-GA (Ngatchou et al. 2015) and DE-BBO (Hybrid Differential Evolution-Biography Based Optimization) which can be used for complex problems.
In this study, the TLBO-Jaya hybrid algorithm was used to be completed all requirements. TLBO has two phases which are known as Teaching (Eqs. (9) and (10)) and the Learning phase. All two phases have different equations to reach and compare objective functions. In order to generate a Hybrid Algorithm, equations of the learning phase are removed by equations of Jaya algorithms, which are illustrated in Eq. (11). TF is known as the teaching factor, $X_{i,\text{new}}$ is a new value, $X_{i,j}$ is a candidate solution's value, $X_{i,a}$ and $X_{i,b}$ are chosen randomly, $X_{i,g_{\text{best}}}$ is an objective function's best value, $X_{i,g_{\text{worst}}}$ is an objective function's worst value.

$$TF = \text{round}(1 + \text{rand}()) \tag{9}$$

$$X_{i,\text{new}} = X_{i,j} + \text{rand}()\left(X_{i,g_{\text{best}}} - |X_{i,j}|\right) - (TF)X_{i,\text{mean}}) \tag{10}$$

$$X_{i,\text{new}} \begin{cases} AF_a < AF_b, \quad X_{i,j} + \text{rand}()(X_{i,a} - X_{i,b}) \\ AF_a > AF_b, \quad X_{i,j} + \text{rand}()(X_{i,b} - X_{i,a}) \\ \downarrow \\ X'_{i,\text{new}} = X_{i,j} + \text{rand}()(X_{i,g_{\text{best}}} - |X_{i,j}|) - \text{rand}()(X_{i,g_{\text{worst}}} - |X_{i,j}|) \end{cases} \tag{11}$$

The optimization process should be carried out in a certain stage, and these stages should be created as complementary and validating each other. This process commonly consists of four stages.

- Process 1: Variables, constraints and constants are determined. Constraints can be specified from standards, former studies or laboratory results. Constants consist of material features and cost values. After that, an initial matrix of recorded data is created.
- Process 2: The best and worst value in the objective function is selected, and the mean value of the objective function is computed to be used in the equations.
- Moreover, minimum and maximum values are checked whether they provide or not. If they do not provide the limitations, the objective function is penalized with big values. Therefore, the new solution matrix is generated.
- After that, the aforementioned processes are found in phase 2.
- Process 3: The objective function in the new solution matrix and the initial matrix are compared with each other, and whichever has the better value is chosen.
- Process 4: The maximum iteration numbers are checked whether they are totally completed. Therefore, the optimization process is decided whether to be continued or not.

Fig. 4 is created to illustrate how the problem can be solved by using a Hybrid Algorithm which is generated by using metaheuristic algorithms known as TLBO and Jaya Algorithm. Flowchart delineates when problem equations, constants and constraints should be used consecutively. Therefore, it is explicitly seen that this chart enables us to find and recognize easily which sequence it should be done.

Multi-objective functions are employed for multiple conflicting objectives that are required to be optimized simultaneously. Therefore, a multi-objective function endeavours to reach a set of solutions that are optimal concerning multiple objectives. These objective functions can be varied in terms of fields that are engineering design, portfolio optimization as well as environmental planning. They are used for minimizing production costs, minimizing environmental impact, minimizing product weight and maximizing production speed. More important properties are chosen to reach optimum results so that appropriate design is obtained easily and effectively.

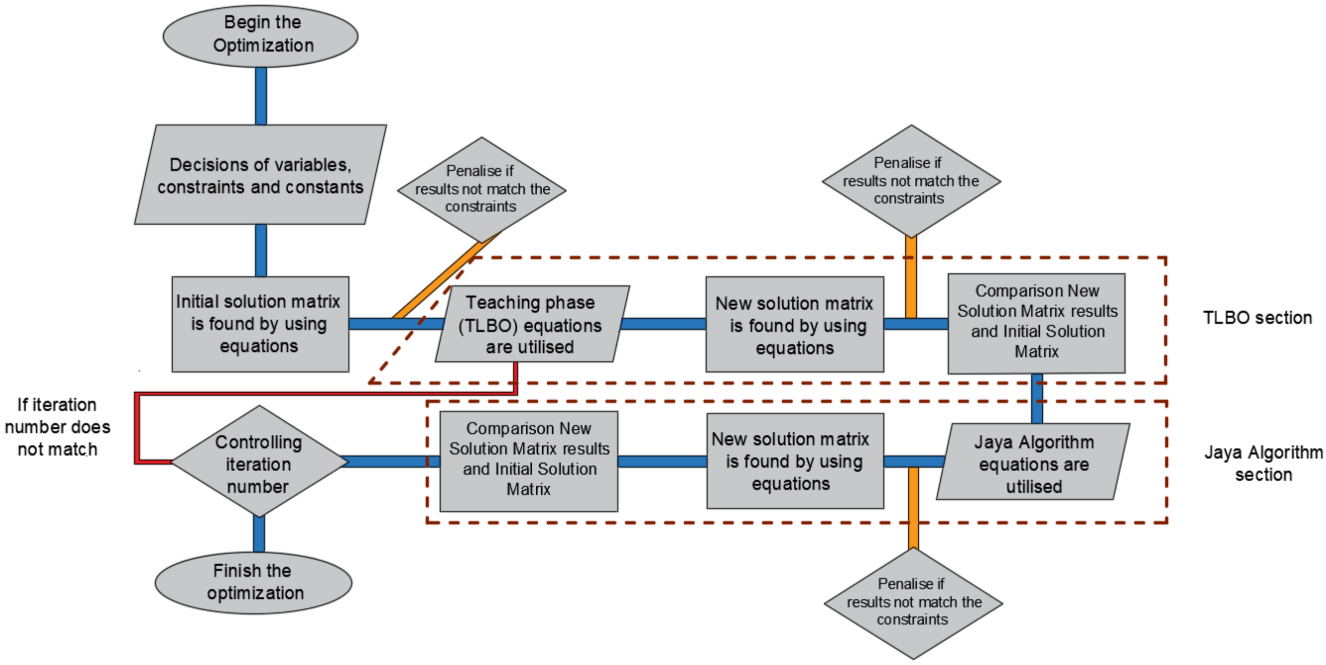

Fig. 4. Flowchart for hybrid algorithm.

Multi-objective optimization has not only a single optimal solution but also a set of optimal solutions which is known as the Pareto-optimal set, and it consists of every potential solution to the problem (Ngatchou et al. 2015). The optimal set of Pareto is an important concept in multi-objective optimization because it enables decision-makers to identify the best compromise between the different objectives (Martinez-Iranzo et al. 2009).

The cost equations are demonstrated in Eqs. (12) and (13). Cost hinges on some factors which are concrete and steel cost (C_c and C_s respectively), beam length (L), cross-section of the beam (b and h) as well as reinforcement area (A_s).

$$\text{Cost}_{\text{concrete}} = C_c \times L \times \left(b \times h - \left(\frac{A_{s,\text{Total}}}{10^6}\right)\right) \tag{12}$$

L_s is recorded as the rebar length, γ_s is the specific density of steel.

$$\sum\nolimits_{i=1} \text{Cost}_{\text{steel}} = C_{s,i} \times L_{s,i} \times \gamma_s \times \frac{A_{s,i}}{10^6} \tag{13}$$

The CO_2 emission equations are delineated in Eq. (14). E_{CO_2} is the CO_2 emission value for materials, V_c is the volume of concrete.

$$\sum \text{CO}_2 = C_c \times V_c \times E_{\text{CO}_2(c)} + \gamma_s \times \frac{A_s}{10^6} \times E_{\text{CO}_2(s)} \tag{14}$$

CO_2 emission and cost are the main goals to generate this problem. Thus, Eq. (15) shows the total values of CO_2 and cost with coefficients. These coefficients can arrange the rate of objective function elements, so they enable us to compare differences between values by changing coefficient values. α and β are not chosen as minus values.

$$f_{\text{total}} = \alpha \times (\text{Cost}_{\text{Total}}) + \beta \times (\text{CO}_{2,\ \text{Total}}) \tag{15}$$

Fig. 5 describes multi-objective function processes which are related to CO_2 and cost, and they are calculated as various rates to reach the best solution for desired situations.

4. Example and Discussion

4.1. Numerical example

In order to apply a sustainable and environmentally friendly design, the objective function is specified not only as a cost but also CO_2 emission. These designs are indispensable and crucial for nature. Therefore, the optimization process is done by using metaheuristic algorithms which are generally used for various problems to achieve desired design values. The design was done as pertinent not only to standards but also necessary shear load.

Fig. 6 shows the beam which is used in the numerical example to reach the objective function. The beam design variables are found depending on distributed load, length of the beam, concrete class, cost of materials and amount of materials' CO_2.

Table 1 illustrates the values which are the variables, constraints along with constants. Furthermore, cost values are current values.

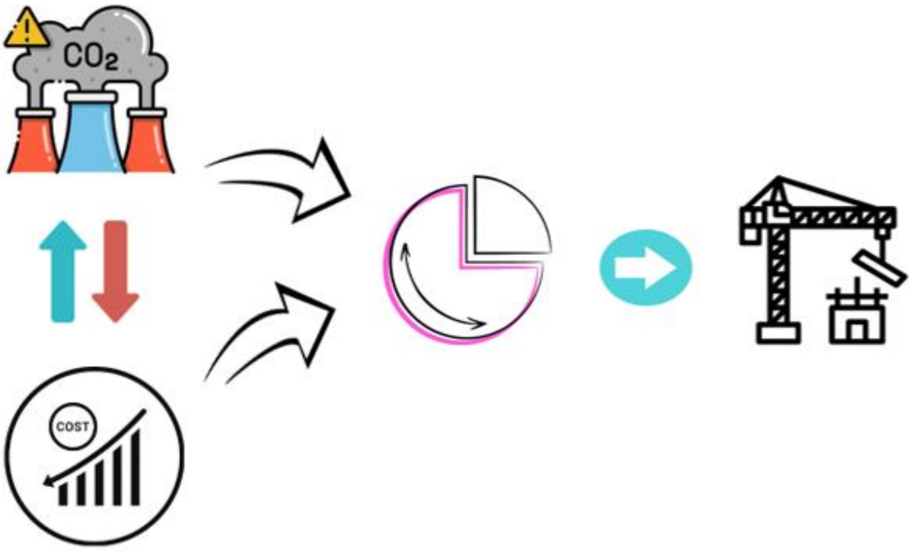

Fig. 5. Multi-objective function example.

Table 1. Numerical example values.

Explanation	Symbol	Unite	Values
Minimum height	h_{min}	mm	400
Maximum height	h_{max}	mm	600
Minimum width	b_{min}	mm	250
Maximum width	b_{max}	mm	400
Compressive strength of concrete	f_{ck}	MPa	30, 40
Length of Beam	L	m	6
Yield strength of concrete	f_{yk}	MPa	420
Specific density of steel	γ_s	t/m³	7.86
Clear cover	P_c	mm	30
Concrete cost per unit volume	C_c	TL/m³	30 MPa →2065 40 MPa →2301
CO_2 emission of concrete values	C_{CO_2}	kg/m³	30 MPa →376 40 MPa →452
Steel cost per unit weight	C_s	TL/ton	Ø>Ø12→16300 Ø10→16600 Ø8→16750

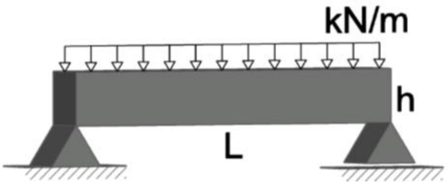

Fig. 6. Illustration of the beam.

Fig. 7 demonstrates the cost of the materials which are the concrete classes and different types of steel. Ø8 and Ø10 are used for stirrups which are necessary for shear force, building standards have some studies about the placement of the clear distance between stirrups. Also, Ø12 and bigger than this rebar is used for longitudinal reinforcement.

Fig. 8 provides information about the CO_2 emission of materials. There are two types of steel which are recycled and not-recycled. These materials impact CO_2 emission, and it is calculated that not-recycled steel is approximately 5 times higher than recycled ones. Some studies give information that not-recycled steel's CO_2 emission changes between 1,800 and 2,000 kg/ton.

4.2. Discussion

According to the numerical example, variables, constraints and constants with equations, an appropriate design is generated in terms of rebar diameters and impact rates of CO_2 and cost in the objective function value. Impact rates were varied in the cases and these are named as Case 1, Case 2 and Case 3. Tables 2 to 6 delineate the results which change according to the diameter of the rebar. Moreover, three cases are generated to compare the rate results between CO_2 emission and cost.

- Case 1 is a 0.5 rate for cost and 0.5 rate for CO2 emission
- Case 2 is a 0.3 rate for cost and 0.7 rate for CO2 emission
- Case 3 is a 0.1 rate for cost and 0.9 rate for CO2 emission

For Table 2, Case 1 and Case 2 have the same results except for objective functions which are different because of rate values, whereas Case 3 variables are different compared to other cases. Fig. 9 shows the results of Table 2.

All cases have the same values in Table 3 except for objective functions. Fig. 10 shows the Table 3 results.

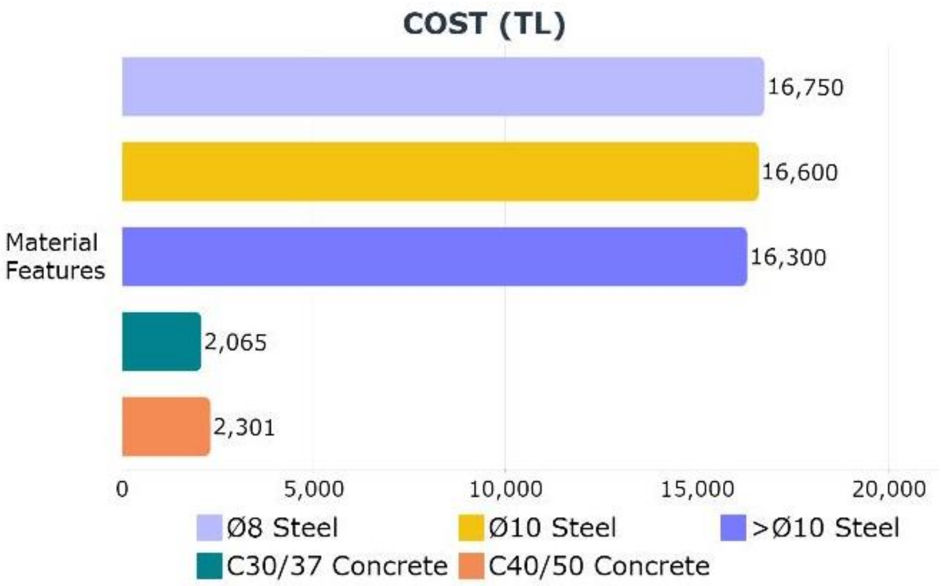

Fig. 7. Cost values.

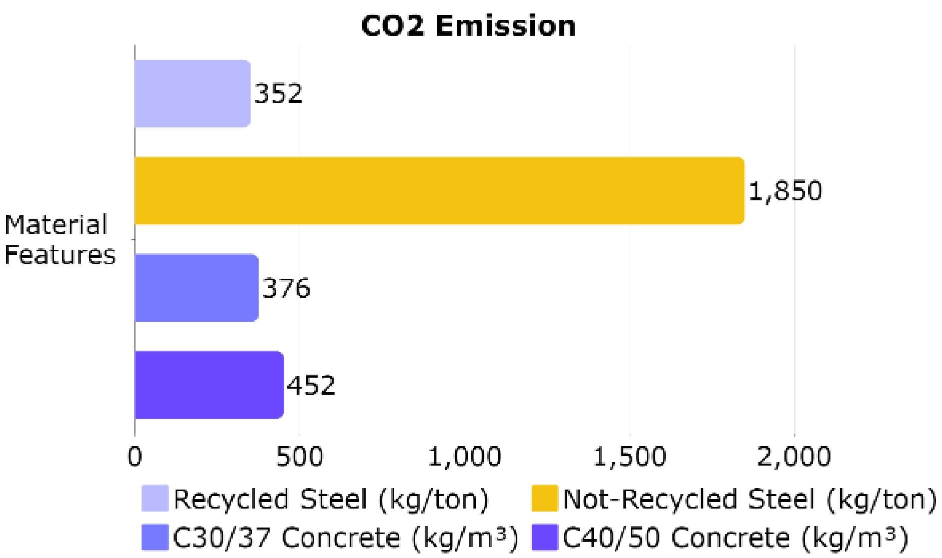

Fig. 8. CO_2 emission values.

Table 2. Ø12 rebar results.

	b	*h*	Reinforcement Area	Concrete Cost	Steel Cost	CO_2 Emission	Objective Function
Case 1	298.67	599.13	678.58	2166.83	1312.85	431.73	1955.71
Case 2	298.67	599.13	678.58	2166.83	1312.85	431.73	1346.12
Case 3	340	521.92	791.68	2146.99	1368.17	429.58	738.14

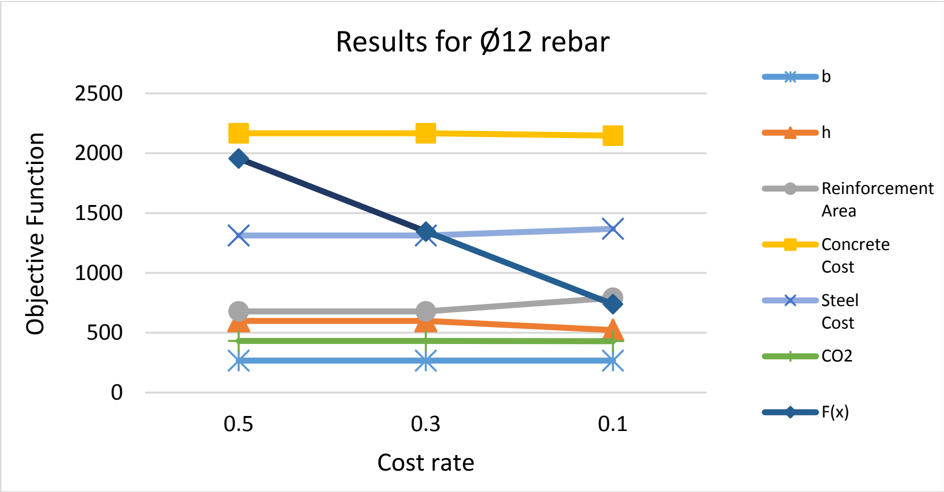

Fig. 9. Results for Ø12 rebar.

Table 3. Ø14 rebar results.

	b	*h*	Reinforcement Area	Concrete Cost	Steel Cost	CO_2 Emission	Objective Function
Case 1	267.33	541.30	769,69	1741.56	1304.31	354.35	1700.11
Case 2	267.33	541.30	769.69	1741.56	1304.31	354.35	1161.81
Case 3	267.33	541.30	769.69	1741.56	1304.31	354.35	623.50

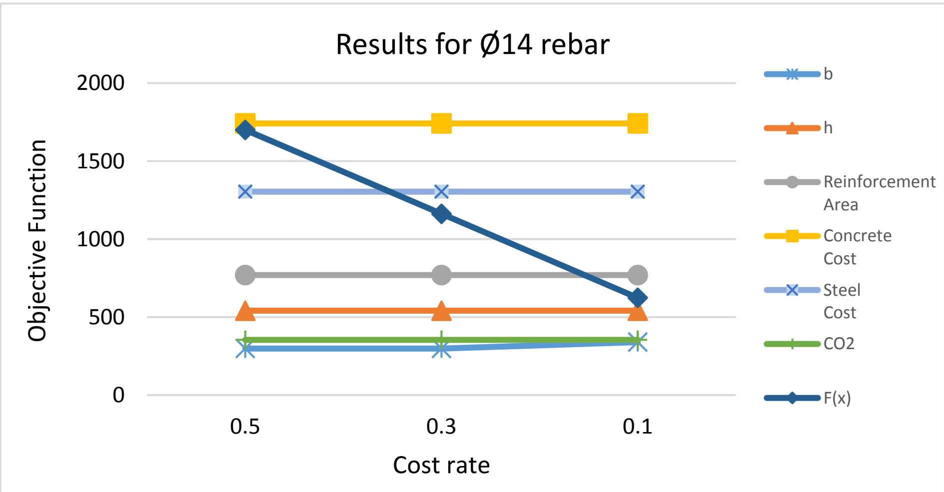

Fig. 10. Results for Ø14 rebar.

It can obviously be seen that Case 2 and Case 3 have the same results, but Case 1 has different results in Table 4. Furthermore, all cases and diameters of rebar have different objective functions which hinge on cost, CO_2 emission as well as the rate between cost and CO_2 emission (Fig. 11). That is why they are generally found different values.

Table 4. Ø16 rebar results.

	b	*h*	Reinforcement Area	Concrete Cost	Steel Cost	CO_2 Emission	Objective Function
Case 1	250.00	524.17	804.25	1571.81	1300.50	323.45	1597.88
Case 2	277.36	436.63	1005.31	1446.03	1402	303.21	1066.66
Case 3	277.36	436.63	1005.31	1446.03	1402	303.21	557.69

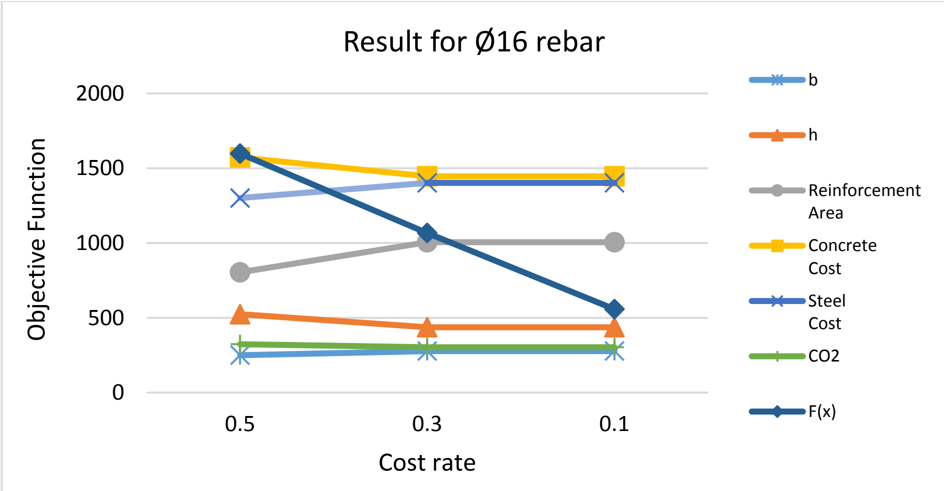

Fig. 11. Results for Ø16 rebar.

Table 5 shows the results of Ø18 rebar and all cases have the same values, it is just objective functions are different. This circumstance is the same as in Table 6. Figs. 12 and 13 display the Table 5 and Table 6 results, respectively.

Table 5. Ø18 rebar results.

	b	*h*	Reinforcement Area	Concrete Cost	Steel Cost	CO_2 Emission	Objective Function
Case 1	250.00	436.89	1017.88	1298.80	1387.80	276.14	1481.37
Case 2	250.00	436.89	1005.31	1298.80	1387.80	276.14	999.27
Case 3	250.00	436.89	1005.31	1298.80	1387.80	276.14	517.18

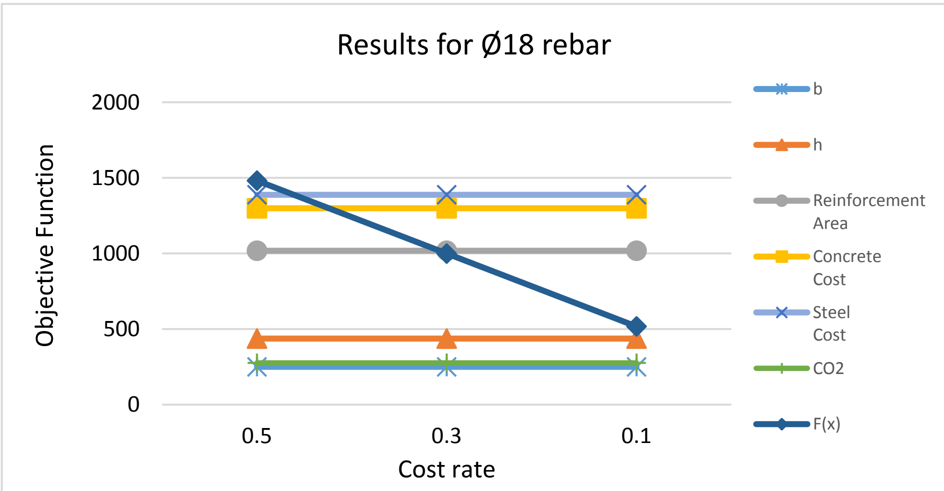

Fig. 12. Results for Ø18 rebar.

Table 6. Ø20 rebar results.

	b	*h*	Reinforcement Area	Concrete Cost	Steel Cost	CO_2 Emission	Objective Function
Case 1	250.00	400.00	1256.64	1180.61	1552.15	258.89	1495.83
Case 2	250.00	400.00	1256.64	1180.61	1552.15	258.89	1001.05
Case 3	250.00	400.00	1256.64	1180.61	1552.15	258.89	506.28

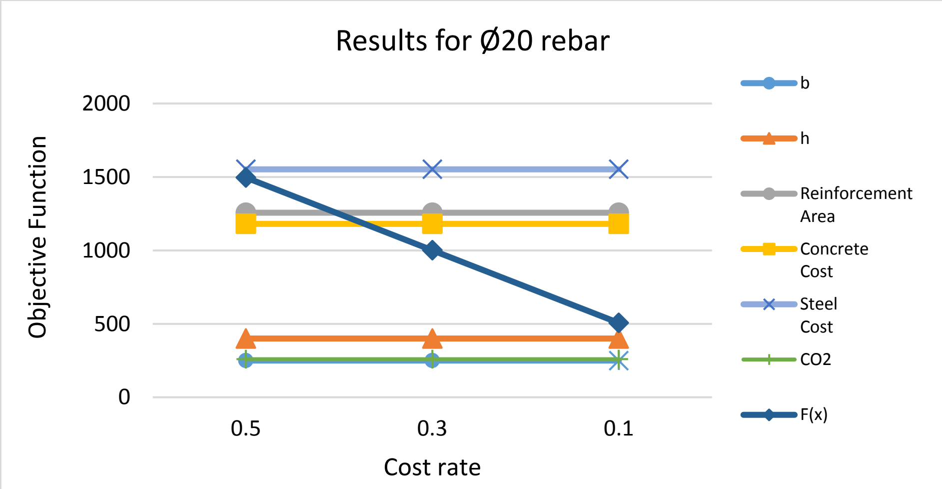

Fig. 13. Results for Ø20 rebar.

The objective function results that are regarding with diameter of steel and steel types that are recycled and not-recycled are demonstrated in Fig. 14. It observed that the differences between recycled and not recycled steel results can be various compared to cases which are "0.5 × cost + 0.5 x CO_2 ; 0.3 × cost + 0.7 × CO_2 ; and 0.1 × cost + 0.9 × CO_2".

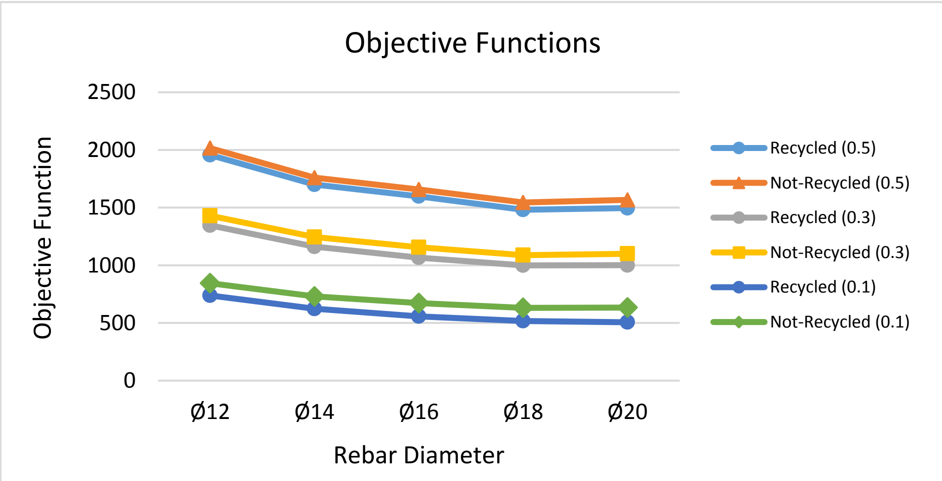

Fig. 14. Comparing objective functions.

That the rate of the cost is chosen as 0.5 for recycled and not-recycled steel has the lowest gap compared to other cases. When the rate s are compared within themselves, different values will be between 3% and 14.4%.

5. Conclusions

Sustainable and environmentally friendly designs are becoming more and more important day by day. One of the biggest reasons for this is that the destruction of nature has increased dramatically in the last few years. Civil engineering, which is one of the fields with a very high CO_2 emission, is at the forefront of the studies carried out and developed. In this context, there are different studies such as materials, optimization and recycling of used materials. In this study, the cost and CO_2 emission optimization for the beam, which is used extensively as a structural element, is carried out with a hybrid algorithm. Such studies are needed in order to use both environmentally friendly and balanced raw materials used in the world. According to certain material, cost and emission values, analyses were made by placing the stirrup and longitudinal reinforcements for the beam both in accordance with the standards and for the shear force. In addition to these analyses, a correlation was established between CO_2 emissions and cost by importance coefficients. With these coefficients, it was ensured that the CO_2 emission value was added to the calculations and used at a higher impact rate than the cost, and comparisons were made. In this way, the reduction of CO_2 emission in the design was provided extra.

Two types of steel were used in the design, one is recycled steel and the other is non-recyclable steel. When these steels are used, analyses were made according to the CO_2 values they emit to nature and the values were recorded. While no difference was observed in the design variables in general, it was observed that there was an increase in the CO_2 emission value. When cases and steel types were compared among themselves, values between objective functions were found between 3% and 14.4%.

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.

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Conflict of Interest

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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.

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