Challenge Journal of CONCRETE RESEARCH LETTERS

Vol.11 No.2 (2020)

acoustic emission artificial neural network compressive strength concrete corrosion cracking curing ductility durability energy absorption ferrocement flaky aggregate fly ash fracture mortar palm oil fuel ash reinforced concrete scrap self-compacting concrete silica fume strengthening superplasticizer tensile strength waste disposal water absorption w[illegible]ility

TULPAR ACADEMIC PUBLISHING

ISSN 2548-0928

Challenge Journal of Concrete Research Letters

E-mail: *cjcrl@challengejournal.com*

Web page: *cjcrl.challengejournal.com*

TULPAR Academic Publishing
www.tulparpublishing.com

Challenge Journal of Concrete Research Letters

CONTENTS

TULPAR ACADEMIC PUBLISHING

Challenge Journal of Concrete Research Letters

Research Article

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

Serdar Ulusoy [a], Aylin Ece Kayabekir [b], Gebrail Bekdaş [b,*], Sinan Melih Nigdeli [b]

[a] Department of Civil Engineering, Turkish-German University, 34820 İstanbul, Turkey
[b] Department of Civil Engineering, İstanbul University-Cerrahpaşa, 34320 İstanbul, Turkey

ABSTRACT

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

ARTICLE INFO

Article history:
Received 2 April 2020
Accepted 3 May 2020

Keywords:
Reinforced concrete
Metaheuristic algorithms
Optimum design
Minimum cost
Strength of concrete

1. Introduction

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

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

* *Corresponding author*. Tel.: +90-212-4737070 ; Fax: +90-212-4737180 ; E-mail address: bekdas@istanbul.edu.tr (G. Bekdaş)
ISSN: 2548-0928 / DOI: https://doi.org/10.20528/cjcrl.2020.02.001

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

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

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

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

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

2. Methodology

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

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

2.1. Harmony Search (HS)

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

2.2. Bat Algorithm (BA)

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

2.3. Teaching-Learning-Based Optimization (TLBO)

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

Table 1. Pseudo code of BA.

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

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

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

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

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

3. Numerical Examples

In the numerical examples, the design having the optimum material cost, including concrete and steel bar for reinforced concrete (RC) beams under the effect of the different bending moment (250 kNm and 500 kNm) are investigated. Also, the effect of different compressive strength of concrete such as 20 MPa, 25 MPa, 30 MPa, 35 MPa and 40 MPa. The cost difference for 5 MPa increase of strength is taken as 5 $/m³.

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

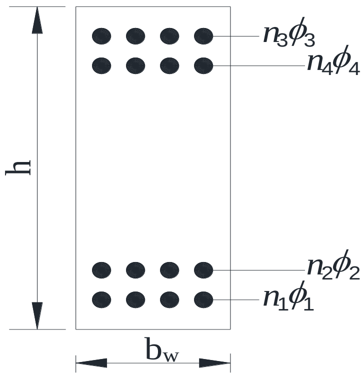


Fig. 1. Design variables of RC beam.

Table 2. Design constants for RC beam.

Design constant	Value
Concrete cover (mm)	35
Maximum aggregate diameter (mm)	16
Compressive strength of concrete (MPa)	20-40
Yield strength of steel (MPa)	420
Stirrup diameter (mm)	10
Unit concrete cost ($/m³)	30-50
Unit steel cost ($/ton)	400
Range of longitudinal steel bars (mm)	10-30
Range of beam breadth (b) (mm)	250-400
Range of beam height (h) (mm)	300-500

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

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

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

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

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

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

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

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

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

4. Conclusions

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

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

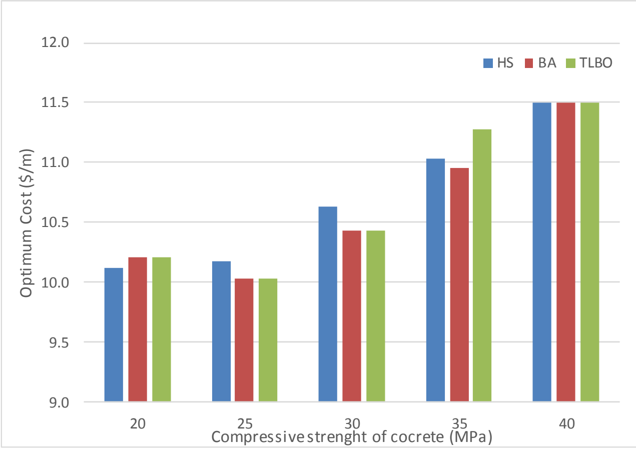


Fig. 2. The optimum costs for 250 kNm flexural moment.

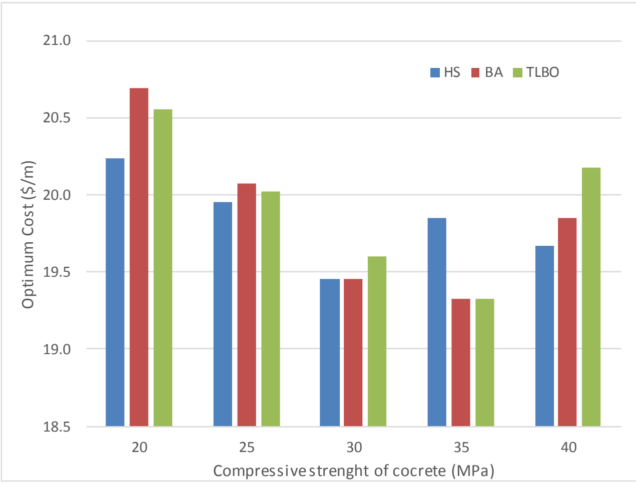


Fig. 3. The optimum costs for 500 kNm flexural moment.

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

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

References

ACI 318M-05 (2005). Building code requirements for structural concrete and commentary. American Concrete Institute.

Akin A, Saka MP (2010). Optimum Detailed Design of Reinforced Concrete Continuous Beams using the Harmony Search Algorithm, In: B.H.V. Topping, J.M. Adam, F.J. Pallarés, R. Bru, M.L. Romero, (Editors), *Proceedings of the Tenth International Conference on Computational Structures Technology*, Civil-Comp Press, Stirlingshire, UK, Paper 131.

Bekdaş G, Nigdeli SM (2013). Optimization of T-shaped RC flexural members for different compressive strengths of concrete. *International Journal of Mechanics*, 7, 109-119.

Bekdaş G, Nigdeli SM (2014a). Optimization of slender reinforced concrete columns. *85th Annual Meeting of the International Association of Applied Mathematics and Mechanics*, 10-14 March 2014, Erlangen, Germany.

Bekdaş G, Nigdeli SM (2014b). Optimization of RC frame structures subjected to static loading. *11th World Congress on Computational Mechanics*, 20-25 July 2014, Barcelona, Spain.

Bekdas G (2014). Optimum design of axially symmetric cylindrical reinforced concrete walls. *Structural Engineering and Mechanics*, 51(3), 361-375.

Bekdaş G (2015). Harmony Search algorithm approach for optimum design of post-tensioned axially symmetric cylindrical reinforced concrete walls. *Journal of Optimization Theory and Applications*, 164(1), 342-358.

Camp CV, Akin A (2012). Design of retaining walls using big bang–big crunch optimization. *Journal of Structural Engineering-ASCE*, 138(3), 438-448.

Camp CV, Huq F (2013). CO_2 and cost optimization of reinforced concrete frames using a big bang-big crunch algorithm. *Engineering Structures*, 48, 363-372.

Camp CV, Pezeshk S, Hansson H (2003). Flexural design of reinforced concrete frames using a genetic algorithm. *Journal of Structural Engineering-ASCE*, 129, 105-11.

Ceranic B, Freyer C, Baines RW (2001). An application of simulated annealing to the optimum design reinforced concrete retaining structure. *Computers and Structures*, 79, 1569-1581.

Coello CC, Hernandez FS, Farrera FA (1997). Optimal design of reinforced concrete beams using genetic algorithms. *Expert Systems with Applications*, 12, 101-108.

Ferreira CC, Barros MHFM, Barros AFM (2003). Optimal design of reinforced concrete T-sections in bending. *Engineering Structures*, 25, 951-964.

Geem ZW, Kim JH, Loganathan GV (2001). A new heuristic optimization algorithm: Harmony Search. *Simulation*, 76, 60-68.

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(6), 963-979.

Kaveh A, Abadi ASM (2011). Harmony Search based algorithms for the optimum cost design of reinforced concrete cantilever retaining walls, *International Journal of Civil Engineering*, 9(1), 1-8.

Leps M, Sejnoha M (2003). New approach to optimization of reinforced concrete beams. *Computers and Structures*, 81, 1957-1966.

Nigdeli SM, Bekdaş G (2014a). Optimum design of RC columns according to effective length factor in buckling. *The Twelfth International Conference on Computational Structures Technology*, 2-5 September 2014, Naples, Italy.

Nigdeli SM, Bekdaş G (2014b). Optimization of reinforced concrete shear walls using Harmony Search. 11th International Congress on Advances in Civil Engineering, 21-25 October 2014, Istanbul, Turkey.

Nigdeli SM, Bekdaş G, Kim S, Geem ZW (2015). A Novel Harmony Search based optimization of reinforced concrete biaxially loaded columns. *Structural Engineering and Mechanics*, 54(6), 1097-1109.

Rafiq MY, Southcombe C (1998). Genetic algorithms in optimal design and detailing of reinforced concrete biaxial columns supported by a declarative approach for capacity checking. *Computers and Structures*, 69, 443-457.

Rajeev S, Krishnamoorthy CS (1998). Genetic Algorithm–based methodology for design optimization of reinforced concrete frames. *Computer-Aided Civil and Infrastructure Engineering*, 13, 63-74.

Paya I, Yepes V, Gonzalez-Vidosa F, Hospitaler A (2008). Multiobjective optimization of concrete frames by simulated annealing. *Computer-Aided Civil and Infrastructure Engineering*, 23, 596-610.

Paya-Zaforteza I, Yepes V, Hospitaler A, Gonzalez-Vidosa F (2009). CO_2-optimization of reinforced concrete frames by simulated annealing. *Engineering Structures*, 31, 1501-1508.

Perea C, Alcala J, Yepes V, Gonzalez-Vidosa F, Hospitaler A (2008). Design of reinforced concrete bridge frames by heuristic optimization. *Advances in Engineering Software*, 39, 676-688.

Rama Mohan Rao AR, Shyju PP (2010). A meta-heuristic algorithm for multi-objective optimal design of Hybrid Laminate Composite Structures. *Computer-Aided Civil and Infrastructure Engineering*, 25(3), 149-170.

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.

Sahab MG, Ashour AF, Toropov VV (2005). Cost optimisation of reinforced concrete flat slab buildings. *Engineering Structures*, 27, 313-322.

Talatahari S, Sheikholeslami R, Shadfaran M, Pourbaba M (2012). Optimum design of gravity retaining walls using charged system search algorithm. *Mathematical Problems in Engineering*, 2012, 1-10.

Yang XS (2010). A new metaheuristic bat-inspired algorithm. In: *Nature Inspired Cooperative Strategies for Optimization (NICSO 2010)*, Springer Berlin Heidelberg, 65-74.

Yepes V, Alcala J, Perea C, Gonzalez-Vidosa F (2008). A parametric study of optimum earth-retaining walls by simulated annealing. *Engineering Structures*, 30, 821-830.

Challenge Journal of Concrete Research Letters

Research Article

Reliability analysis of a reinforced concrete bridge under moving loads

Hakan Bayrak [a,*], Ferhat Akgül [b]

[a] *Department of Civil Engineering, Kafkas University, 36100 Kars, Turkey*
[b] *Department of Engineering Sciences, Middle East Technical University, 06531 Ankara, Turkey*

ABSTRACT

This study presents a reliability analysis procedure for a reinforced concrete bridge exposed to different moving loads. Bridges are one of the important part of transportation infrastructure systems. As bridges age, structural weakening due to heavy traffic and aggressive environmental factors lead to an increase in repair frequency and decrease in load carrying capacity. Therefore, bridges require periodic maintenance and repair in order to function and be reliable throughout their lifetimes. In other words, condition and safety of the bridges must be monitored at regular time intervals to avoid the disadvantages of deterioration. Otherwise, sudden collapse of a bridge may lead to irreversible loss of life and property. Therefore, the importance of the structural assessment of bridges is rapidly increasing in developed countries. In this study, reliability analysis which is one of the structural performance prediction method is applied to a reinforced concrete bridge subjected to the different moving loads. The aim of this study is to observe the safety of the bridge for the effect of the increasing traffic factor over the years.

ARTICLE INFO

Article history:
Received 18 April 2020
Accepted 21 May 2020

Keywords:
Reinforced concrete bridges
Reliability index
Probability of failure
Structural assessment
First order reliability method

1. Introduction

Infrastructure systems are essential facilities for communities and countries because they supply the necessary transportation, water and energy utilities. Because of increasing populations, more facilities are being constructed to meet demand for these systems. Increasing number of infrastructure systems leads to results in encountering the most important problems allocating sufficient funds and making appropriate decision for maintenance and repair to ensure their survival and serviceability during the lifetime period. In addition, aging and environmental factors create more needs for periodic inspection, maintenance and repair of these systems. Furthermore, the process of planning and design are invariably made under conditions of uncertainty and risk is often unavoidable. In addition, there are various causes of performance deterioration of a structural system. Particularly, in reinforced concrete bridges, deterioration is caused by corrosion and the main reason for corrosion in concrete is the chloride diffusion into concrete leading to corrosion of steel reinforcement. The causes of deterioration of performance may be grouped into three main categories. Kong (2001) stated that they include the aging (reduction of resistance and increase in loading), special actions (collusions by vehicles, earthquakes, pollution, etc.) and human errors. Existence of deterioration may have a major impact on the serviceability and load carrying capacity of bridges. For instance, small amount of local corrosion in prestressing steel cables of prestressed reinforced concrete beams may cause a sudden collapse in the structure. Therefore, the infrastructure management systems are needed to monitor the condition and safety of structural systems over the years. One of the infrastructure management systems is the Bridge Management Systems (BMSs) because bridges are one of the crucial part of the transportation infrastructure systems. After unexpected failures of certain bridges have occurred such as the Silver Bridge in the U.S, researchers focused on creating BMSs to establish

* *Corresponding author*. Tel.: +90-474-225-1657 ; Fax: +90-474-225-1282 ; E-mail address: hbayrak@kafkas.edu.tr (H. Bayrak)
ISSN: 2548-0928 / DOI: https://doi.org/10.20528/cjcrl.2020.02.002

maintenance and repair programs and to record the condition of bridges. Thompson et al. (1998) developed a well-known and most used bridge management system in the world. Also, Hawk and Small (1998) created another bridge management system to enable the allocation of resources for repair and maintenance of bridges. In other words, the aim of BMSs is to implement the best maintenance and repair strategies ensuring an adequate level of reliability at the lowest possible life-cycle cost.

In developed countries for the structural assessment of bridges, structural safety criterion is the most important criterion among the other criteria taken into account which affects the determination of investment budgets of bridge maintenance and repair. Safety is a function of combinations of loads over the lifetime of the structure. Furthermore, structural safety depends on the load carrying capacity of the structure. However, structural deterioration of reinforced concrete bridges decreases their load carrying capacities. Therefore, the assessment of remaining load carrying capacity of bridges is crucial part in management of bridge structures. In addition, performance prediction of an infrastructure system is a difficult process due to existence of many uncertainties. Mori and Ellingwood (1993) studied on uncertainties in the deterioration initiation time of a bridge structure. Hence, deterioration prediction models are produced to overcome this difficulty. The condition-based and safety-based performance prediction methods used by BMSs are two different procedures to give an idea about the structural safety. Unlike the condition-based structural assessment which is generally performed visually, structural assessment normally requires structural engineering formulations or determination of quantified value of resistance degradation and load increase in a bridge member. Reliability index β or probability of failure P_f can be used as a performance indicator to quantify the structural safety. Actually, reliability analysis method is one of the procedure used for safety prediction approaches in developed countries to conduct the structural assessment of bridges. Reliability index β and probability of failure P_f concepts are introduced in the following section.

2. Reliability Analysis

Reliability analysis methods are subject of the mechanical studies based on probability. In other words, probabilistic measure of assurance of performance is defined as reliability. Prediction of structural reliability is generally based on either the calculation of reliability index or the probability of failure. As an alternative criterion to the probability of failure, reliability index has been more often used as a measure for bridge elements and systems. Reliability can be formulated as the determination of the capacity of the system to meet certain requirements. This way, probabilistic nature of structural capacity and load can be modeled using the supply capacity (resistance) and the demand requirement (load) terms presented by R and Q, respectively. The objective of the reliability analysis is to ensure the event $R>Q$ throughout the lifetime of the structure. This is possible only if the probability event $P(R>Q)$ is satisfied. Fig. 1 shows the relative probability distributions of resistance R of a structural element and load impact Q.

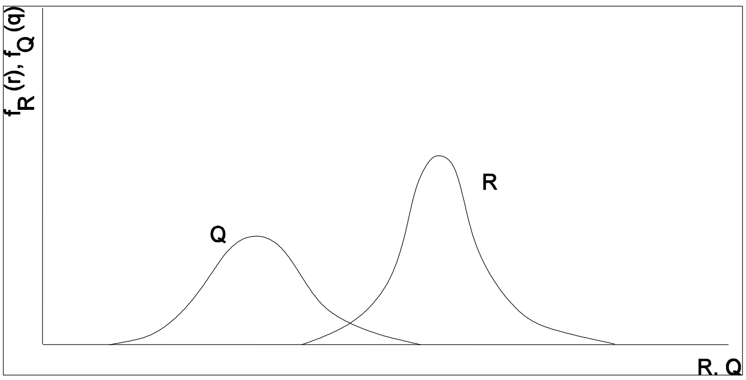


Fig. 1. Probability distributions of strength R and load impact Q.

Load and resistance have a time dependent effect on probability of failure throughout the service life of structure. Indeed, expected resistance of a structure decreases in time because of environmental factors, whereas load impact on a structure increases in time. Probability of failure can be defined as the probability that the resistance is less than the load, which is formulated as Eq. (1).

$$P_f = \int_{-\infty}^{\infty}\left[1 - F_Q(x)\right]f_R(x)dx \qquad (1)$$

This integral is not generally solved by analytical. Frangopol et al. (2004) generated a number of method to approximate the probability of failure. In addition, failure probability is used to obtain the reliability index of the structural system. Here, probability of occurrence of $R>Q$ is calculated by integration known as reliability of the structural element (probability of safety, P_s) which is defined by the area under the joint probability distribution function $f_{R,Q}(r,q)$ shown as in Eq. (2).

$$P_s = P(R > Q) = P(R - Q > 0) = \iint_{R>Q} f_{R,Q}(r,q)drdq \qquad (2)$$

The term R-Q defines another random variable which is called as Safety Margin and shown by M. The safety margin consists of resistance variable R and load variable Q.

The mean and standard deviation of M are shown by μ_M and σ_M, respectively. If R and Q are normally distributed random variables, there is a direct relationship between the probability of failure and reliability index. Then Eq. (3) can be formulated as:

$$P_f = P(R - Q \leq 0) = P(M \leq 0) = \Phi\left(-\frac{\mu_M}{\sigma_M}\right) \quad (3)$$

In Eq. (3), the value of ϕ which is the cumulative distribution function of standard normal variable can be found in any standard normal distribution table. The value, within the parenthesis of ϕ function, is called the safety index by Cornell (1969). Also, this ratio is called as reliability index β shown in Eq. (4).

$$\beta = \frac{\mu_M}{\sigma_M} \quad (4)$$

The probability of occurrence of any event in statistics is between 0 and 1. Therefore, probability of safety in terms of the probability of failure is defined as shown in Eq. (5). In addition, probability of safety is defined in terms of reliability index as shown in Eq. (6).

$$P_S = 1 - P_f \quad (5)$$

$$P_s = \Phi(\beta) \quad (6)$$

Using the description of safety margin, for normally distributed random variables, the reliability index formula can be extended as in Eq. (7).

$$\beta = \frac{\mu_R - \mu_Q}{\sqrt{\sigma_R - \sigma_Q}} \quad (7)$$

Safety margin equation described above M=R-Q is called as performance function g(x) which defines limit state M=0 as well is defined as thus. The vector X contains the random variables in limit state function. g(x) describes the limit state of the system, g(x)<0 defines failure state, and however g(x)>0 represents safety state. In reliability analysis, Christensen (1998) introduced performance functions considering failure modes for bridges.

Structural systems are composed of structural members. In addition, capacity of the systems is affected by the capacity and formation of the members. There are three types of structural systems according to combination of topologies and configuration of structural components, namely; series, parallel, and the combination of series and parallel systems. The safety or failure of these systems are determined by formulas according to system types. Enright and Frangopol (1998) studied on system reliability for reinforced concrete highway girder bridges with time-dependent resistance and loads. The study considered environmental factors to predict the reliability of reinforced concrete bridges. Estes and Frangopol (1999) proposed a system reliability approach for optimizing the lifetime repair strategy for highway bridges. In their study, the bridge was modeled as a series-parallel combination of failure modes, limit-state equations were developed for each failure mode in terms of certain random variables, and the reliability with respect to occurrence of each possible failure mode was computed separately based on these limit-state equations using First Order Reliability Method (FORM). In addition, Hong (2000) studied on taking into account the correlation between the failures of structural elements for the system reliability. Furthermore, Estes and Frangopol (2001) demonstrated that a component whose reliability index is below the target reliability level may not cause the reliability of the system to fall below the target reliability. If components of the systems are connected in series, such systems are called series systems and the failure of these systems requires failures of any one of the components. In other words, the reliability or safety of the system requires that none of the components fail. If components of the systems are connected in parallel, such systems are called parallel systems and the total failure of these systems requires failures of all components. In other words, the system remains safe if any one of the components survives. On the other hand, many structures in reality include a combination of series and parallel systems as illustrated in Fig. 2, where each number designates a failure mode or a component of a system. Also, bridges are examples of combination of series and parallel structural systems. In multi span bridges, the spans are in series connections with each other. Furthermore, each span consists of elements that form a parallel system in itself.

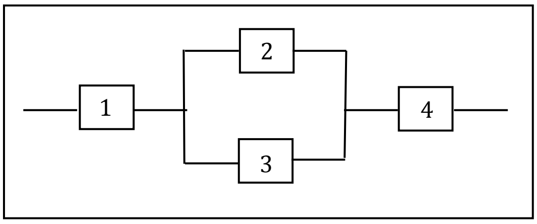


Fig. 2. A combined series-parallel system.

Failure of combination of series and parallel systems are formulated shown in Eq. (8). Here, the terms n and m show the number of series and parallel components in the structural system, respectively. Eq. (8) shows that the total failure of a system requires failure of any one of the series elements or failure of all parallel components. For instance, in Fig. 2, system fails when the components numbered 1 or 4 fails. In addition, system fails when both components numbered 2 and 3 fail together. Otherwise, the system remains safe and continue to survive.

$$P_f = P\left(\cup_{k=1}^{n} \cap_{j=1}^{m_i} \{g_{ij}(x) < 0\}\right) \quad (8)$$

When the bridge superstructure elements are considered, the limit state equations are different for the deck and girders. In addition, limit state equations are determined for every structural components according to their failure modes. For instance, different limit state equations are determined by considering the bending moment and shear force. Akgül and Frangopol (2004) and (2005) developed the limit state equations of bridge elements for different bridge types. According to solution of limit state functions, there are two different reliability method. These are the First Order Reliability Method (FORM) and the Second Order Reliability Method (SORM). In FORM, limit state functions are linearized and then solved. Also, FORM can be solved in an iterative manner. The formulations consist of theoretical essentials of FORM were presented by Ang and Tang (1984). On the other hand, SORM is a method based on a quadratic approximation to limit state function.

3. Analysis of a Reinforced Concrete Bridge

Behavior of civil infrastructure systems is predicted using structural assessment methods. In this study, reliability analysis method is applied to an example reinforced concrete bridge aiming to predict the performance level of the bridge. The concrete material is found easily in the most areas of the world and has high flexibility. Furthermore, reinforced concrete bridges provide sufficiently earthquake-resistance performance and appropriate long-term maintenance cost. Also, reinforcing the concrete gives an important ability to bridges for crossing the appropriate openings. Therefore, the reinforced concrete bridge is one of the most preferred bridge type. In this study, a multi span reinforced concrete bridge is chosen as an exemplary bridge built by Turkish General Directorate of Highways to cross the stream in the end of 1960s. The chosen bridge was designed with 4 spans and 8 number of I profiles were used in cross-section of the bridge. Total length of the bridge is 44 meters. Both length of inner spans are 12 meters. Also, length of outer spans is 10 meters. In addition, steel ST 37 and concrete Wb28 225 have been used in construction of the bridge. In this study, the system failure model is constituted by considering the superstructure of the bridge consisting of decks and girders. Also, the First Order Reliability Method is used to calculate the reliability index for the reinforced concrete bridge. The reliability index β calculated is compared to the target reliability index β_T which is the minimum reliability index for the structure to be safe. The limit state functions and bridge span length affect the value of target reliability index shown as in Table 1. In this study, target reliability index for analysed bridge is selected as 3.5 according to ASSHTO (1992).

Table 1. Target reliability indices according to bridge properties.

Bridge Type	Span length	Girder spacing	Target Reliability Index
All type	~10 m	~1.2 m	between 2 and 4
Steel girders and reinforced concrete T-beams	~(20-60 m)	-	between 3 and 4
Prestressed concrete girders	-	-	~5

In order to perform reliability analysis, firstly, structural analysis was conducted and the loads to which the bridge was exposed were calculated. The bridge was designed by the Turkish General Directorate of Highways according to H15-S12 truck load. In this study, two different moving loads are acted on the bridge to observe the safety of the bridge for the effect of the increasing traffic factor over the years. The selected moving loads are H15-S12 and H20-S16 truck loads. Load characteristics of both vehicles are given in the Table 2. Analysis carried out for the design load of the bridge and the results obtained from the design load as H15-S12 truck were represented in Figs. 3 and 4. The bridge was analyzed by loads at supports called as C, D, E and at spans called as F, G because of having a structural symmetry. Moving load resulted by truck passing over the bridge was distributed to girders of the bridge using moving load distribution factor and impact factor according to American Association of State Highway and Transportation Officials – Live and Resistance Factor Design, Live Load Distribution Specifications, AASHTO (1994).

Table 2. Vehicles load characteristics.

Load class	H15-S12	H20-S16
Weight, kN	150	200
Concentrated load for moment, kN	67.5	90
Concentrated load for shear, kN	97.5	135
Distributed load, kN/m	7.5	10

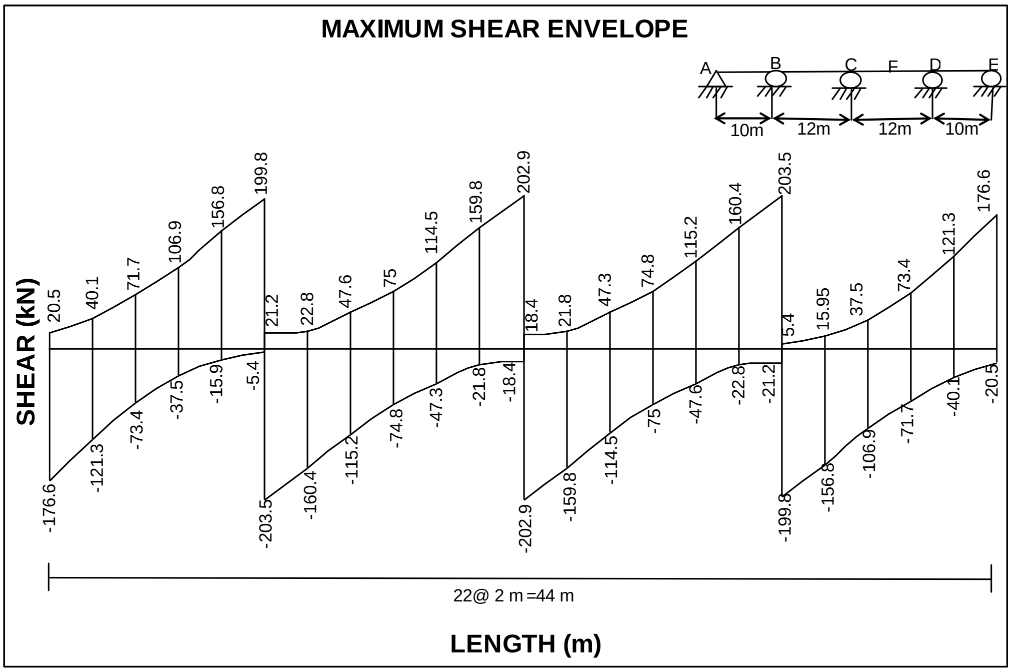


Fig. 3. Maximum shear envelope for H15-S12 truck load.

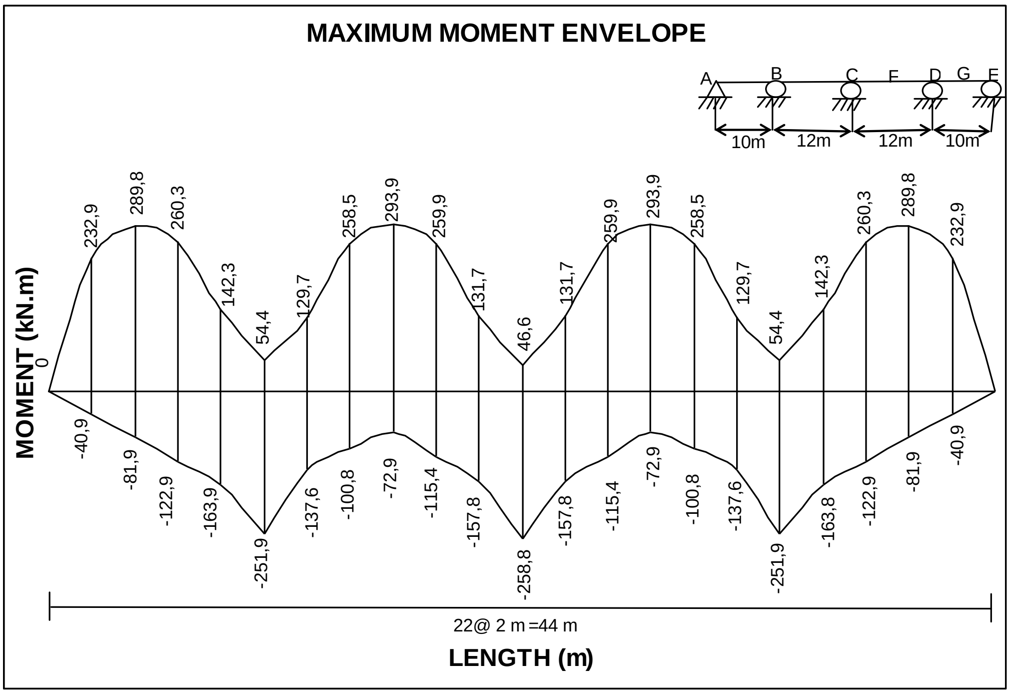


Fig. 4. Maximum moment envelope for H15-S12 truck load.

3.1. Calculation of reliability index

The shear force capacity and moment capacity are calculated by multiplying nominal capacity values of the cross-section with 1,1 shown in Eqs. (9) and (10). Also, the structural analysis results for shear force and moments capacity are presented in Table 3.

$$\overline{M_R} = 1{,}1 \times M_{n,cap} \tag{9}$$

$$\overline{V_R} = 1{,}1 \times V_{n,cap} \tag{10}$$

The moving load due to the vehicles passing over the bridge is distributed to the girders on the bridge by using the live load distribution factor and the impact factor as shown in Eqs. (11-13).

$$D_f = \frac{S}{5{,}5} \tag{11}$$

In Eq. (11), D_f is the live load distribution factor and its approximate value for the analysed bridge is 0.182. S is the distance between the two adjacent girders. In addition, live load shear force and moment which applied to girders are calculated as in Eqs. (12) and (13). Here, I is the impact factor and assumed as 1.3 in calculations.

$$\overline{M_{LL}} = M_{LL} \times I \times D_f \tag{12}$$

$$\overline{V_{LL}} = V_{LL} \times I \times D_f \tag{13}$$

In the probabilistic reliability analysis, the coefficient of variation (COV) values generally varies from 0.05 to 0.30 according to the variables denoted by Frangopol (1999). In this study, COV values used for variables are shown in Table 4.

Finally, reliability index of the bridge for shear force and moment were calculated by using Eq. (7) taking into account unknowns of capacity, dead load and moving load shown in Tables 5 and 6.

Table 3. Structural analysis results for H15-S12 truck load.

	Support C	Span F	Support D	Span G
Shear force capacity (kN)	5156.8	5156.8	5156.8	5156.8
Dead load shear (kN)	48.45	0.253	-50.5	-9.94
Moving load shear (kN)	202.9	-75	203.5	176.6
Moment capacity (kN.M)	683.28	683.28	683.28	683.28
Dead load moment (kN.M)	-96.4	48.19	-99.43	51.75
Moving load moment (kN.M)	-258.8	293.9	-251.9	289.8

Table 4. Coefficient of variation (COV) for the variables (%).

COV values	Used values	Range
Capacity	10	5-15
Dead load	5	5-10
Moving load	20	15-30

Table 5. Reliability Indices at supports and spans based on design load for shear force.

	Support C	Span F	Support D	Span G
Shear force capacity (kN)	5156.8	5156.8	5156.8	5156.8
Dead load shear (kN)	48.45	0.253	-50.5	-9.94
Moving load shear force (kN)	48	-17.75	48.15	41.78
Variance of shear force capacity (kN)	265925.86	265925.86	265925.86	265925.86
Sum of variance of loads (kN)	315.26	112.5	321.5	264.4
Reliability index (β)	11.21	13.55	10.75	12.23

Table 6. Reliability Indices at supports and spans based on design load for moment.

	Support C	Span F	Support D	Span G
Moment capacity (kN.M)	683.28	683.28	683.28	683.28
Dead load moment (kN.M)	-96.40	48.19	-99.43	51.75
Moving load moment (kN.M)	-61.23	69.55	-59.60	63.78
Variance of moment capacity (kN.M)	4668.99	4668.99	4668.99	4668.99
Sum of variance of loads (kN)	173.20	199.30	166.80	169.50
Reliability index (β)	7.55	8.11	7.54	8.16

Reliability index β for the shear force capacity was calculated based on the analysis results for truck H15-S12 regarding standard normal distribution table. The smallest reliability index for shear capacity is obtained at support D as 10.75. The value 10.75 of reliability index pairs with the value 0.25E-15 of probability of failure and this value of the probability of failure is very small. Also, reliability index value is much bigger than selected target reliability value. This situation implies that the bridge is in safe according to shear capacity.

As shown in Table 6, reliability index β for the moment capacity was calculated based on the analysis results for truck H15-S12 and probability of failure of the bridge was calculated based on β values and regarding standard normal distribution table. As seen, the smallest reliability index is obtained at support D as 7.54. The value 7.54 of reliability index pairs with the value 0.20E-13 of probability of failure and this value of the probability of failure is also very small. In addition, reliability index value is much bigger than the selected target reliability value. Therefore, under the design load, the bridge is in safe for moment capacity.

The bridge decreasing its strength in time is exposed to the more load than the design one as well. Therefore, the second analysis was performed for heavier load than the design load of the bridge and the structural analysis results of H20-S16 truck acted to the bridge are represented in Table 7.

The analysis procedure for the results of H15-S12 truck is repeated this time for the results of H20-S16 truck by using Eqs. (9)-(13). Finally, the new reliability indices of the bridge for shear force and moment according to H20-S16 truck load were calculated by using Eq. (7) taking into account unknowns of capacity, dead load and moving load shown in Tables 8 and 9.

Reliability index β for shear force capacity was calculated based on the result of analysis for truck H20-S16. The smallest reliability index is obtained at support C and support D as 9.66. As seen, reliability index value obtained from analysis is much bigger than the selected target reliability index. So, this situation implies that the bridge subjected to H20-S16 truck load is in safe according to shear force.

Table 6. Reliability Indices at supports and spans based on design load for moment.

	Support C	Span F	Support D	Span G
Moment capacity (kN.M)	683.28	683.28	683.28	683.28
Dead load moment (kN.M)	-96.40	48.19	-99.43	51.75
Moving load moment (kN.M)	-61.23	69.55	-59.60	63.78
Variance of moment capacity (kN.M)	4668.99	4668.99	4668.99	4668.99
Sum of variance of loads (kN)	173.20	199.30	166.80	169.50
Reliability index (β)	7.55	8.11	7.54	8.16

Table 7. Structural analysis results for H20-S16 truck load.

	Support C	Span F	Support D	Span G
Shear force capacity (kN)	5156.8	5156.8	5156.8	5156.8
Dead load shear (kN)	48.45	0.253	-50.5	-9.94
Moving load shear (kN)	508.4	-243.5	-509.5	-278.83
Moment capacity (kN.M)	683.28	683.28	683.28	683.28
Dead load moment (kN.M)	-96.4	48.19	-99.43	51.75
Moving load moment (kN.M)	-860.3	893.1	-816	886

Table 8. Reliability indices for shear force capacity at supports and spans based on H20-S16 truck load.

	Support C	Span F	Support D	Span G
Shear force capacity (kN)	5156.8	5156.8	5156.8	5156.8
Dead load shear (kN)	48.45	0.253	-50.5	-9.94
Moving load shear force (kN)	120.29	-57.61	-59.60	63.78
Variance of shear force capacity (kN)	265925.86	265925.86	265925.86	265925.86
Sum of variance of loads (kN)	584.76	132.7	587.7	174.5
Reliability index (β)	9.66	9.88	9.66	9.85

Table 9. Reliability indices for moment capacity at supports and spans based on H20-S16 truck load.

	Support C	Span F	Support D	Span G
Moment capacity	683.28	683.28	683.28	683.28
Dead load moment	-96.40	48.19	-99.43	51.75
Moving load moment	-203.55	211.31	-191.10	209.63
Variance of moment capacity	4668.99	4668.99	4668.99	4668.99
Sum of variance of loads	1680.53	1791.90	1516.20	1764.83
Reliability index (β)	4.81	5.27	4.96	5.26

Furthermore, reliability index β for moment capacity was calculated based on the result of analysis for truck H20-S16. The smallest reliability index is obtained at support C as 4.81. Reliability index value obtained from analysis is slightly bigger than the value of selected target reliability index. So, according to the result, the bridge subjected to H20-S16 truck load is in safe for the moment capacity.

4. Conclusions

Reliability index is used as performance indicator for the structures. In this study, reliability index of a reinforced concrete bridge subjected to different moving loads is calculated and the obtained results are compared and discussed. As bridges age, reliability index of bridge decreases due to aggressive environmental factors and heavy traffic load. The values of probability of failure of bridges not applied any maintenance and repair actions increase more and more in time. In addition, decreasing of resistance capacity resulted from aging of bridge is the most important factor causing the failure of a bridge. One of the most important reason of decreasing of the resistance capacity is the structural deterioration over the years. Material degradation models and statistical load increment models are improved in order to estimate how safety index decrease over time. In this study, any material degradation model was not used. Analysis was carried out for the design load and the load heavier than the design load to illustrate the effect of increasing traffic load in time.

The difference between reliability index obtained from the H20-S16 truck load and the reliability index obtained from the design load is compared with each other. The smallest reliability index obtained from design load is 7.54 and it has changed dramatically and reached to 4.81 which is very close to the target reliability index under H20-S16 truck load. The results of conducted analysis indicate that if the bridge is not subjected to any maintenance or repair activities for many years, the load carrying capacity of the bridge may decrease leading to sudden collapse of the bridge. Also, the analysis results revealed how important Bridge Management Systems are, especially in countries with high number of bridges. As a future work, a material degradation model and a performance deterioration model may be generated and applied to obtain the more accurate value of the reliability index of a bridge system.

References

Akgül F, Frangopol DM (2004). Lifetime performance analysis of existing steel girder bridge superstructures. *Journal of Structural Engineering, American Society of Civil Engineers,* 130(12), 1875-1888.

Akgül F, Frangopol DM (2005). Lifetime performance prediction of existing reinforced concrete bridges, I: Theory. *Journal of Infrastructure Systems, American Society of Civil Engineers*, 11(2), 122-128.

Ang AH-S, Tang WH (1984). Probability Concepts in Engineering Planning and Design, Vol. II, Decision, Risk, Reliability. John Wiley & Sons, Inc., New York, USA.

ASSHTO (1992). Standard Specifications for Highway Bridges, American Association of State Highway and Transportation Officials, Wash, DC, USA.

ASSHTO (1994). LRFD Bridge Design Specifications, American Association of State Highway and Transportation Officials, Wash, DC, USA.

Christensen PT (1998). Assessment of the reliability profiles for concrete bridges. *Journal of Engineering Structures*, 20, 1004-1009.

Cornell CA (1969). A probability based structural code. *Journal of American Concrete Institute*, 66(12), 974-985.

Enright MP, Frangopol DM (1998). Probabilistic analysis of resistance degradation of reinforced concrete bridge beams under corrosion, *Engineering Structures,* 20(11), 960-971.

Estes AC, Frangopol DM (1999). Repair optimization of highway bridges using system reliability approach. *Journal of Structural Engineering, ASCE*, 125(7), 766-775.

Estes AC, Frangopol DM (2001). Bridge lifetime system reliability under multiple limit states. *Journal of Bridge Engineering*, 125(7), 766-775.

Frangopol DM (1999). Bridge Safety and Reliability. American Society and Civil Engineers, Reston, USA.

Frangopol DM, Kallen MJ, and van Noortwijk JM (2004). Probabilistic models for life-cycle performance of deteriorating structures: review and future directions. *Progress in Structural Engineering and Materials*, 6, 197-212.

Hawk H, Small EP (1998). The bridgit bridge management system. *Structural Engineering International*, 8(4), 308-314.

Hong HP (2000). Assessment of reliability of aging reinforced concrete structures. *Journal of Structural Engineering*, 126(12), 1458-1465.

Kong JS (2001). Lifetime maintenance strategies for deteriorating structures. *Ph.D thesis*, University of Colorado, Boulder, Colorado, USA.

Mori Y, Ellingwood BR (1993). Reliability-based service-life assessment aging concrete structures. *Journal of Structural Engineering*, 119(5), 1600-1621.

Thompson PD, Small EP, Johnson M, Marshall A (1998). The Pontis bridge management system. *Structural Engineering International*, 8(4), 303-308.

Challenge Journal of Concrete Research Letters

Research Article

Investigation of optimal designs for concrete cantilever retaining walls in different soils

Esra Uray [a,*], Serdar Çarbaş [b], İbrahim Hakkı Erkan [c], Murat Olgun [c]

[a] *Department of Civil Engineering, KTO Karatay University, 42020 Konya, Turkey*
[b] *Department of Civil Engineering, Karamanoğlu Mehmetbey University, 70100 Karaman, Turkey*
[c] *Department of Civil Engineering, Konya Technical University, 42250 Konya, Turkey*

ABSTRACT

In this paper, the investigation of the optimum designs for two types of concrete cantilever retaining walls was conducted utilizing the artificial bee colony algorithm. Stability conditions like safety factors of sliding, overturning and bearing capacity and some geometric instances due to inherent of the wall were considered as the design constraints. The effect of the existence of the key in wall design on the objective function was probed for changeable properties of foundation and backfill soils. In optimization analysis, the concrete of the wall, which directly affects parameters such as carbon dioxide emission and the cost, was considered as the objective function and analyzes were performed according to different discrete design variables. The optimum concrete cantilever retaining wall designs satisfying constraints of stability conditions and geometric instances were obtained for different soil cases. Optimum designs of concrete cantilever retaining wall with the key were attained in some soil cases which were not found the feasible optimum solution of the concrete cantilever retaining wall. Results illustrate that the artificial bee colony algorithm was a favorable metaheuristic optimization method to gain optimum designs of concrete cantilever retaining wall.

ARTICLE INFO

Article history:
Received 23 April 2020
Accepted 24 May 2020

Keywords:
Concrete cantilever retaining wall
Check for sliding, overturning, and bearing capacity
Optimum design
Discrete design variables
Artificial bee colony algorithm

1. Introduction

In geotechnical engineering, cantilever retaining wall is commonly employed for enduring lateral soil pressure occurred between two different soil levels. Cantilever retaining wall, which comes into existence by combining a base and thin stem, is manufactured utilizing materials like stone, concrete or concrete-reinforcement. Design of a cantilever retaining wall must not be only ensured stability conditions but also should have a low cost. While a designer is trying to meet the requirement of being safe and economical wall design, the effect of changing parameters on the wall design should also be deliberated. In the wall design, considering parameters, for instance, retained height, the existence of groundwater, the physical position of construction area, intended use of the structure, the completion time of the construction and soil properties have made the design process complex with many unknowns. That is why utilizing metaheuristic optimization methods in the solution of this kind of engineering problems has become quite popular in recent years. Metaheuristic optimization methods are algorithms that mimic the behaviours of creatures like the process of survival, foraging, and migration in nature. The metaheuristic optimization methods which does not guarantee the accurate solution are robust and effective by courtesy of approaching the feasible solution in a reasonable time.

Many metaheuristic optimization methods that provide optimum solutions for the complex engineering problems have been presented hitherto; the genetic algorithm (GA) by Goldberg (1989), the particle swarm optimization (PSO) by Kennedy and Eberhart (1995), the ant colony algorithm (ACO) by Dorigo and Gambardella

* *Corresponding author*. Tel.: +90-332-221-7251 ; Fax: +90-332-202-0044 ; E-mail address: esra.uray@karatay.edu.tr (E. Uray)
ISSN: 2548-0928 / DOI: https://doi.org/10.20528/cjcrl.2020.02.003

(1997), the harmony search algorithm (HSA) by Geem et al. (2001), the artificial bee colony algorithm (ABC) by Karaboga (2005), the firefly algorithm (FA) by Yang (2009), and the cuckoo search algorithm (CS) by Rajabioun (2011). The study conducted by Sarıbaş and Erbatur (1996) has been one of the first examples for the optimum cantilever wall design investigated the optimum wall weight and the optimum cost. Since the metaheuristic algorithms are simple, effective, and easy to implement, using these algorithms to analyze the optimum design and cost of cantilever retaining walls have become widespread. Studies for the optimization analysis of cantilever retaining wall were carried out by Camp and Akın (2012), Gandomi (2015), Temur and Bekdaş (2016), and Uray et al. (2019).

In this study, the optimum designs of concrete cantilever retaining wall (CRW) and concrete cantilever retaining wall with key (CRWK) were investigated utilizing the artificial bee colony algorithm. For changing soil instances, obtained optimum designs of CRW and CRWK have been compared in terms of concrete wall weights.

2. Materials and Methods

2.1. Geotechnical design of the concrete cantilever retaining wall designs

The optimum wall design of the concrete cantilever retaining wall (CRW) and the concrete cantilever retaining wall design with key (CRWK) must be provided stability conditions like check for sliding, overturning, and bearing capacity with the allowable safety factors for the safe wall design. The wall dimensions and acting loads to the wall utilized for calculation of the safety factors of sliding, overturning, and bearing capacity in the design of CRW and CRWK were indicated respectively in Figs. 1 and 2.

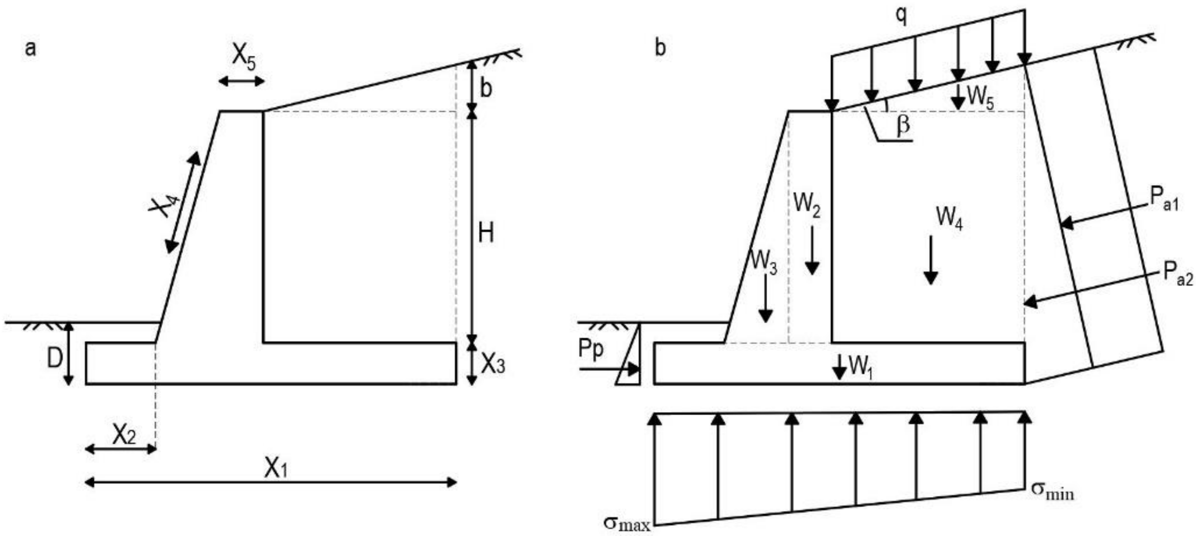


Fig. 1. Concrete cantilever retaining wall design: (a) wall dimensions; (b) acting loads to the wall.

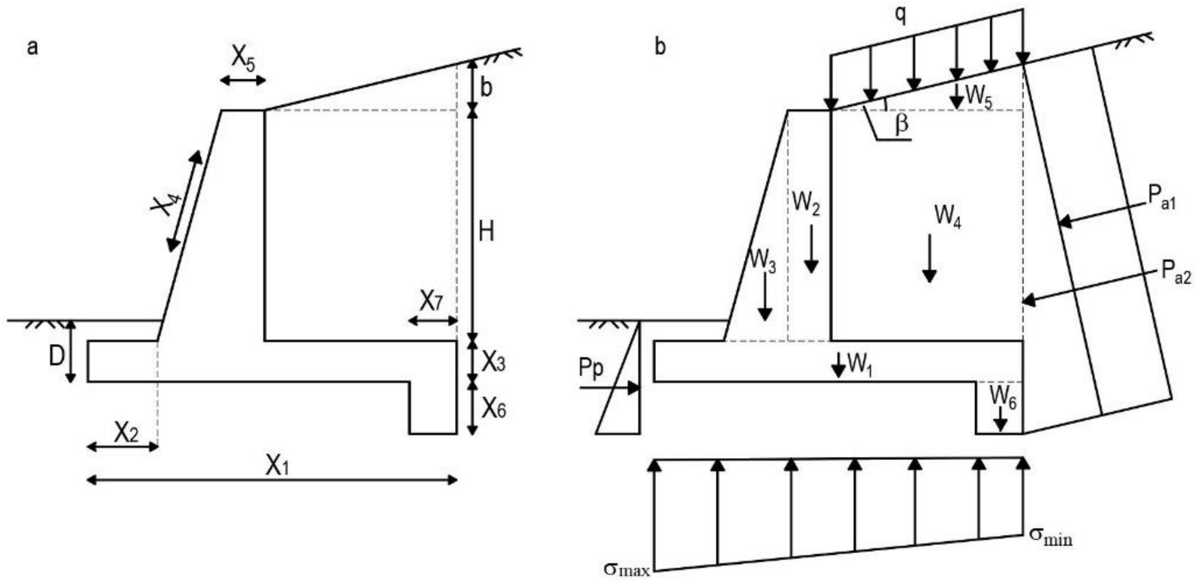


Fig. 2. Concrete cantilever retaining wall design with key: (a) wall dimensions; (b) acting loads to the wall.

While W_1, W_2, W_3, and W_6 correspond to the concrete weight of the wall for CRW or CRWK, W_4 and W_5 sign the soil weight above the back extension of the wall. P_a and P_p are active and passive soil pressure forces, respectively and P_a (Eq. (1)) is equal to the sum of P_{a1} and P_{a2} given in Figs. 1(b) and 2(b).

$$P_a = P_{a1} + P_{a2} = qK_a(b + H + X_3) + 0.5K_a\gamma_{bs}(b + H + X_3)^2 \quad (1)$$

The passive soil pressure force is calculated using Eq. (2) for the CRW design and Eq. (3) for CRWK design. Here, γ_{bs}, γ_{fs} and c_{fs} are the unit volume weights of backfill soil and foundation soil, and cohesion of foundation soil, in turn.

$$P_p = 0.5K_p\gamma_{fs}D^2 + 2c_{fs}\sqrt{K_p}\,D \quad (2)$$

$$P_p = 0.5K_p\gamma_{fs}(D + X_6)^2 + 2c_{fs}\sqrt{K_p}\,(D + X_6) \quad (3)$$

In the determination of active and passive soil pressure coefficients given in Eqs. (4) and (5) Rankine theory (1857) is utilized. In equations, β, $\emptyset_{fs}$, and $\emptyset_{bs}$ correspond to respectively the slope of the backfill soil, the angle of internal friction of the backfill soil and the angle of internal friction of the foundation soil.

$$K_a = \cos\beta\,\frac{\cos\beta - \sqrt{\cos^2\beta - \cos^2\emptyset_{bs}}}{\cos\beta + \sqrt{\cos^2\beta - \cos^2\emptyset_{bs}}} \quad (4)$$

$$K_p = \tan^2\left(\frac{45 + \emptyset_{fs}}{2}\right) \quad (5)$$

In the wall designs, stability criteria which are safety factors of sliding ($F_s(s)$), overturning ($F_o(s)$), and bearing capacity ($F_s(bc)$), have been employed; given in respectively Eqs. (6), (7) and (8) with allowable the minimum and the maximum values of safety factors.

$$F_s(s,\min) \le F_s(s) = \frac{\sum V\tan\left(\frac{2}{3}\emptyset_{fs}\right) + \frac{2}{3}X_1c_{fs} + P_p}{P_a\cos\beta} \le F_s(s,\max) \quad (6)$$

$$F_s(o,\min) \le F_s(o) = \frac{\sum M_r}{\sum M_o} \le F_s(o,\max) \quad (7)$$

$$F_s(bc,\min) \le F_s(bc) = \frac{q_u}{q_{\max}} \le F_s(bc,\max) \quad (8)$$

Eq. (9) has determined the sum of vertical forces ($\sum V$) effective directly on the resistance to sliding for CRW and CRWK. To determine the overturning safety factor rotation effect of acting loads to the wall must be calculated. The total moment ($\sum M_r$) of forces which withstand overturning of the wall according to toe point of the wall base is given Eq. (10) for CRW or CRWK. The total moment ($\sum M_o$) which try to overturn the wall at the toe point is determined as M_o given in Eq. (11).

$$\sum V = \sum W_i + P_a\sin\beta \quad (9)$$

$$\sum M_r = \sum W_ix_i + \cdots + W_6x_6 + P_a\sin\beta X_1 \quad (10)$$

$$\sum M_o = 0.5qK_a(b + H + X_3)^2\cos\beta + 0.5K_a\gamma_{bs}(b + H + X_3)^3/3 \quad (11)$$

The loads coming from the wall (q_{max}) must be safely transferred to the soil by the foundation, and these loads must be carried by the soil (q_u). The minimum base pressure (q_{min}) in the interface between the soil and the wall must be greater than the zero ($e < X_1/6$) as the soil cannot bear the tension. Expressions of q_{max}, q_{min}, and eccentricity (e) are given Eqs. (12) and (13), respectively. General bearing capacity expression suggested by Meyerhof (1963) have been utilized for the calculation of the ultimate bearing capacity (q_u) (Das, 2016).

$$q_{\substack{\min\\ \max}} = \frac{\sum V}{X_1}\left(1 \pm \frac{6e}{X_1}\right) \quad (12)$$

$$e = \frac{X_1}{2} - \frac{\sum M_r - \sum M_o}{\sum V} \quad (13)$$

2.2. Formulation of the optimization problem for the concrete cantilever retaining walls

In the optimization problems generally should have three basic concepts, including the design space, the design constraints and the objective function. The dimensions of CRW are the base width (X_1), the toe extension (X_2), the base thickness (X_3), the inclination of the wall front face (X_4), and the top thickness of the stem (X_5) given in Fig 1(a). The dimensions of CRWK given in Fig. 2(a) which are the base width (X_1), the toe extension (X_2), the base thickness (X_3), the inclination of the wall front face (X_4), and the top thickness of the stem (X_5), the height of key (X_6) and the thickness of key (X_7) were selected as the discrete design variables. To determinate of the lower-the upper bounds for the discrete design variables, wall dimensions suggested in the provisions of Building Code Requirements for Structural Concrete (ACI 318-08, 2008) and LRFD Bridge Design Specifications (AASHTO, 2010) were employed. The lower-the upper bounds of the discrete design variables with increments have been tabulated in Table 1.

The wall designs obtained by using different values of the design variables given in Table 1 must provide these basic four rules for the external stability of the wall: (i) Safety factor of sliding of the wall must be greater than its minimum acceptable value, (ii) Safety factor of overturning of the wall must be greater than its minimum allowable value, (iii) The pressure transferred from the base to the soil must be smaller than the ultimate bearing capacity of the soil, (iv) The eccentricity of resultant force at the base surface must be within in the core not to occur tension stress. Therefore, these rules were defined as design constraints for having values of minimum and maximum safety factors. The minimum safety factors values of sliding, overturning and bearing capacity have been taken as F_s (s, min) = 1.50, F_s (o, min) = 1.50, and F_s (bc, min) = 3.00, respectively (Das, 2016). Also, the maximum safety factors (F_s (s, max), F_s (o, max), F_s (bc, max)) whose changing values depend on soil properties were considered with the aim of obtaining more economical design. Besides, the eccentricity control in base width constraint and geometric design constraints due to the wall dimensions were taken into consideration too in the optimization analyses. Normalized expressions of all design constraints are designated in Table 2.

Table 1. Design variables and limit bounds for CRW and CRWK.

Design variables	Lower bound	Upper bound	Increment
X_1: Base width	$0.25H$	$1.0H$	$0.05H$
X_2: Toe extension	$0.15X_1$	$0.60X_1$	$0.05X_1$
X_3: Base thickness	$0.06H$	$0.15H$	$0.015H$
X_4: Inclination of wall front face (%)	0	6	1
X_5: Top thickness of stem (cm)	0.20	0.40	0.05
X_6: Height of key	$0.60X_3$	$1.20X_3$	$0.10X_3$
X_7: Thickness of key	$0.20X_1$	$0.40X_1$	$0.05X_1$

Table 2. Design constraints.

Design constraints	Normalized expression
The sliding safety factor lower bound	$g_x(1) = 1 - F_s(s)/F_s(s, \min)$
The sliding safety factor upper bound	$g_x(2) = F_s(s)/F_s(s, \max) - 1$
The overturning safety factor lower bound	$g_x(3) = 1 - F_s(o)/F_s(o, \min)$
The overturning safety factor upper bound	$g_x(4) = F_s(o)/F_s(o, \max) - 1$
The bearing capacity safety factor lower bound	$g_x(5) = 1 - F_s(bc)/F_s(bc, \min)$
The bearing capacity safety factor upper bound	$g_x(6) = F_s(bc)/F_s(bc, \max) - 1$
The eccentricity constraint	$g_x(7) = X_1/(6e)$
The geometric constraint 1	$g_x(8) = X_5/(HX_4 + X_5) -1$
The geometric constraint 2	$g_x(9) = (X_2 + HX_4 + X_5)/X_1/-1$

In this paper, the objective function of the optimization problem taken as concrete weight of CRW and CRWK. Wall weights of CRW and CRWK have been compared for different soil conditions. The mathematical expressions of the objective formulation for CRW and CRWK are given Eqs. (14) and (15), respectively.

$$f_{\min} = W_1 + W_2 + W_3 \tag{14}$$

$$f_{\min} = W_1 + W_2 + W_3 + W_6 \tag{15}$$

2.3. Artificial bee colony algorithm

The artificial bee colony algorithm (ABC) suggested by Karaboga (2005) is one of the metaheuristic optimization algorithms. It is inspired by swarm intelligence that is effective interpersonal communication for surviving as a swarm in nature and having basic life needs such as nutrition, defense and migration. General concepts and algorithm steps have given for the artificial bee colony algorithm based on bees' nutritional processes and behaviour in this chapter. Bees tried to find the best food source in the algorithm are divided into three groups; as the employed bees, the onlooker bees and the scout bees. The employed bees seek food source vicinity of the hive and evaluate the quality of a found food source. If this quality is better than the previously found quality of the food source, the location of the food source is kept in their mind. The onlooker bees observe the returned employed bees that dance to share the information like the amount of nectar, quality, and location about the found food source. Factors like the type of dance or time of dancing are influential in selecting which food source is worth to prefer by the onlooker bees. When the food sources are consumed, the process of the employed bee and the onlooker bee is fulfilled. The random seeking of the scout bee commences for the possible food sources around the hive. The scout bee that finds a food source turns into an employed bee. Only one scout bee is allowed, and the number of employed bees is equal to the number of food sources in the algorithm.

In this optimization problem of the wall design, designs of CRW and CRWK with the changeable values of design variables correspond to food sources, and the quality of the food sources are the weights of the wall. The main steps of the ABC algorithm for the optimum design of CRW and CRWK are as follows:

Step 1: The ABC algorithm parameters which are the number of employed bees (*NEB*), the number of onlooker bees (*NOB*), the number of the food source (*NFS*), the number of maximum iteration (*maxiter*), and limit (Akay and Karaboga, 2012) are defined and initial food source areas are formed by using Eq. (16).

$$x_{ij} = x_j^{\min} + \text{rand}(0,1)\left(x_j^{\max} - x_j^{\min}\right)$$
$$(i = 1, \ldots, NFS, j = 1, \ldots, N) \quad (16)$$

Here, N is the total number of design variables. In this study, N has been taken 5 and 7 for designs of CRW and CRWK, respectively. Rand (0,1) means a random number between 0 and 1. $x_j^{\min}$ and $x_j^{\max}$ are given as the lower and the upper bounds of the j^{th} design parameter, respectively. The food matrix (FM) corresponding the design space is formed by using values of design variables given in Table 1 and Eq. (16). For each row of FM, which states wall designs, values of the objective function are calculated.

Step 2: The employed bees determine a new food source and evaluate its quality. In determining a new food source which is neighbor of its current food source Eq.17 is used.

$$v_{ij} = \begin{cases} x_{ij} + \emptyset_{ij}\left(x_{ij} - x_{kj}\right), & \text{rand}(0,1) < MR \\ x_{ij}, & \text{rand}(0,1) \geq MR \end{cases}$$
$$(\emptyset_{ij} = [-1,1]) \quad (17)$$

Here, x_{ij} means the j^{th} design variable randomly selected of the i^{th} food source and k is a randomly chosen value between 1 and NFS. The modification rate, MR, is a control parameter for use in checking a new source is developed or not. The value of MR has been suggested to be between 0.30-0.80 (Akay and Karaboga, 2012). Fitness value for the appropriate new food source (v_{ij}) is calculated by using Eq. (18).

$$\text{fitness}_i = \begin{cases} 1/(1+f_i), f_i \geq 0 \\ 1 + \text{abs}(f_i), f_i < 0 \end{cases} \quad (18)$$

Here, f_i is the objective function value of the new food source. The selection process is performed between x_i and v_i by using Deb's Rules (Deb, 2000) which consider constraint violations of the obtained wall designs (Karaboga and Akay, 2011). If the penalty value of the new wall design is better than the worst penalty value one in mind, the worst wall design replaced with the new wall design. Otherwise, the worst one remains in mind.

Step 3: All employed bees fulfil their seeking in the vicinity of the hive for the food sources and keep in their mind the information about them. In the algorithm, it means new wall designs obtained. Employed bees share information about the food sources like the amount of nectar and location of the food sources on the dance area. To give an idea to the onlooker bees is determined probability values used in a probabilistic selection based on the information of the food sources. The onlooker bees evaluate the transferred information in proportion the calculated values of the fitness and constraint violations of the food sources. Probability of selection of the food source by the onlooker bees is defined in Eq. (19).

$$p_i = \frac{\text{fitness}_i}{\sum_{j=1}^{NFS} \text{fitness}_j} \quad (19)$$

Step 4: The onlooker bees select the food source area using the information provided by the employed bees in this step. If the produced random number within the range [0,1] is greater than the p_i (Eq. (19)), the onlooker bees produce a new food source like the employed bees by using Eq. (17). The new food source and the old food source are compared, and then the better one is selected by using Deb's rules. This process continues until all onlooker bees complete their search for the food sources.

Step 5: It is checked whether the nectar in a food source is exhausted or not when the employed and the onlooker bees complete the cycles. After abandoned food sources are determined by using the limit parameter, scout bee initializes the searching for a new food source by using Eq. (16). This cycle continues until the current iteration number reaches the maximum iteration number, and then the algorithm terminates.

3. Optimization Analyses and Results

The optimum weights of CRW design given in Fig. 1 and CRWK design given in Fig. 2 were obtained by using the ABC algorithm. In the optimization analyses, sixteen variable soil conditions presented in Table 3 which include two different values for the cohesion of foundation soil, two different values for the angle internal friction of the foundation soil, and four different values for the angle of internal friction of backfill soil were taken into consideration as example wall designs. Except for the three above mentioned soil parameters, the other input parameters have been taken the same for all example wall designs.

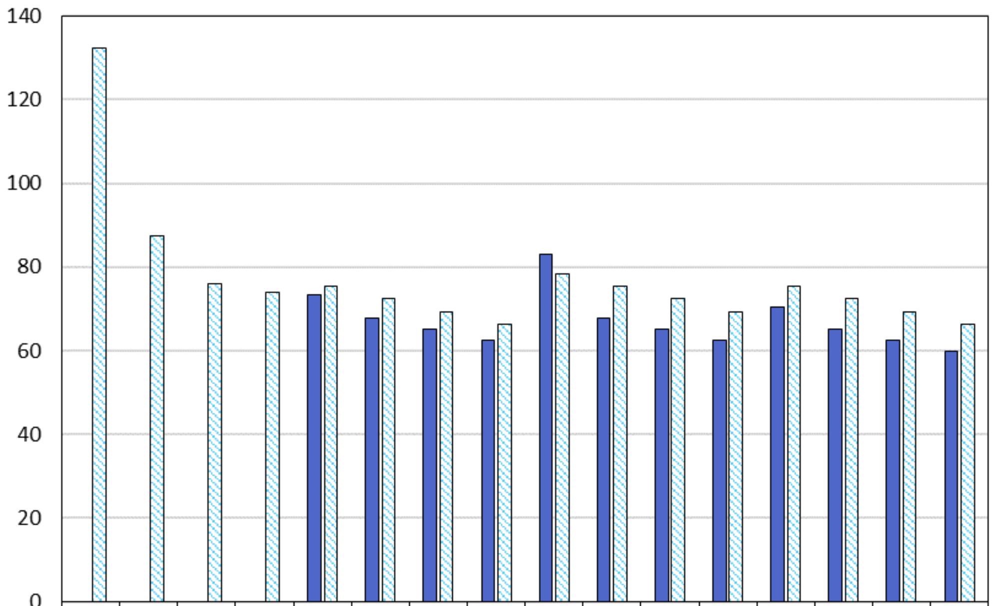
Initial food sources were formed by using Eq. (16) for the design variables demonstrated in Table 1. The values of objective functions by using Eqs. (14) or (15) and penalty values by using design constraints given in Table 2 have been calculated for the wall designs. The ABC algorithm by continuing iterations and cycles achieved the optimum wall design among all possible wall designs, which has the minimum penalty value with the minimum wall weight for current soil condition.

In this study, the algorithm parameters of modification rate, population size, number of the food source, limit and number of maximum iterations were taken as 0.40, 30, 15, NFSxN and 5000, respectively. For each soil condition, the algorithm has been operated in 500 times, by the number of maximum iterations and it also has been observed that the more minimum wall weight cannot be obtained anymore with continuing analysis of the cycles. The optimum wall weights are demonstrated in Fig. 3 for the various soil conditions.

Fig. 3 illustrates that the optimum wall weights decrease with the increasing the angle of internal friction of the backfill soil and the cohesion of the foundation soil for all angle of internal friction of the foundation soil ($\emptyset_{bs}$). The feasible wall the feasible wall design satisfied the design constraints was attained only for CRWK design in the soil condition $\emptyset_{bs}$=20-35°, $\emptyset_{fs}$=20° and c_{fs}=50 kPa. The CRW weight was smaller than the CRWK weight when the values of the cohesion of the foundation soil and the angle of internal friction of the backfill soil were the minima ($Ø_{bs}$=20°, $Ø_{fs}$=30°and c_{fs}=50kPa). There is no conclusion that CRWK designs are less costly than CRW designs for other soil conditions.

Table 3. Parameters of example wall designs.

Input parameter		Unit	Symbol	Value
Height of stem		m	H	6
Surcharge load		kPa	q	20
Backfill slope		°	β	10
Depth of foundation		m	D	0.50
Unit weight of foundation soil		kN/m³	γ_{fs}	19
Unit weight of backfill soil		kN/m³	γ_{bs}	18
Unit weight of concrete		kN/m³	γ_c	25
Cohesion of backfill soil		kPa	c_{bs}	0
Cohesion of foundation soil	Case 1	kPa	c_{fs}	50
	Case 2	kPa	c_{fs}	100
Internal friction angle of foundation soil	Case 1	°	$Ø_{fs}$	20
	Case 2	°	$Ø_{fs}$	30
Internal friction angle of backfill soil	Case 1	°	$Ø_{bs}$	20
	Case 2	°	$Ø_{bs}$	25
	Case 3	°	$Ø_{bs}$	30
	Case 4	°	$Ø_{bs}$	35



	Øfs=20° cfs=50kPa				Øfs=20° cfs=100kPa				Øfs=30° cfs=50kPa				Øfs=30° cfs=100kPa			
	Øbs= 20°	Øbs= 25°	Øbs= 30°	Øbs= 35°	Øbs= 20°	Øbs= 25°	Øbs= 30°	Øbs= 35°	Øbs= 20°	Øbs= 25°	Øbs= 30°	Øbs= 35°	Øbs= 20°	Øbs= 25°	Øbs= 30°	Øbs= 35°
CRW	0.00	0.00	0.00	0.00	73.20	67.80	65.10	62.40	83.10	67.80	65.10	62.40	70.50	65.10	62.40	59.70
CRWK	132.2	87.38	76.12	73.81	75.36	72.34	69.31	66.29	78.38	75.36	72.34	69.31	75.36	72.34	69.31	66.36

Fig. 3. Optimum wall weights for the various soil conditions.

In the investigation of the optimum wall designs, lower-upper bounds of the safety factors have been selected to obtain the safe and economical design. Safety factors of sliding, overturning and bearing capacity, for wall design examples are shown in Fig. 4. The lower (F_s (s, min), F_s (o, min), F_s (bc, min)) and the upper (F_s (s, max), F_s (o, max), F_s (bc, max)) bounds of safety factors for different soil conditions have been demonstrated at the same figure with the red lines.

It is evident from Fig. 4 while obtained optimum wall designs were satisfied with the lower bounds of safety factors.

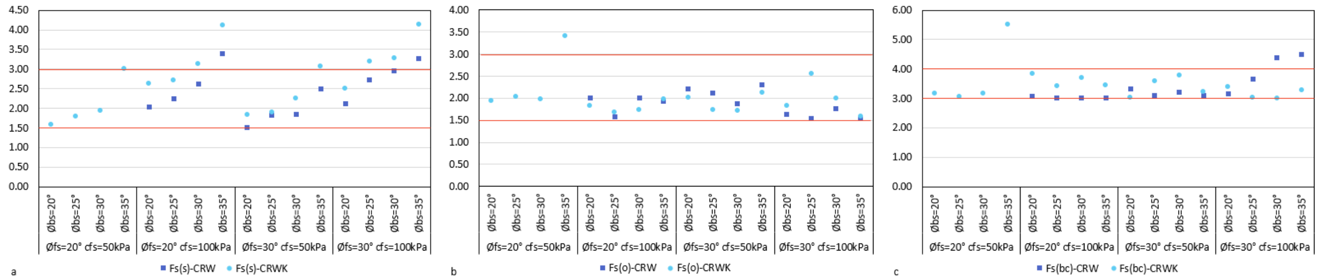


Fig. 4. Safety factors of example wall designs: a) sliding; b) overturning; c) bearing capacity.

4. Conclusions

In this study, the optimum designs of concrete cantilever retaining walls have been investigated using the artificial bee colony algorithm, an effective optimization technique that has been widely applied to engineering problems. The wall dimensions of concrete cantilever retaining wall (CRW) and the concrete cantilever retaining wall with the key (CRWK) satisfied stability conditions have been attained to find the minimum wall weight. According to the result of the optimization analysis, the costs of CRW and CRWK designs have growth when the angle of internal friction of the foundation soil is smaller than 25°. CRWK design is more economical than CRW design just for poor foundation soil. Adding a key to the concrete cantilever retaining wall is insignificant in terms of obtaining the more economical wall designs for quality foundation soil. Consequently, it is observed that the artificial bee colony algorithm can be effectually used in obtaining the optimum concrete retaining wall designs.

References

ACI 318-08 (2008). ACI Committee 318, Building Code Requirements for Structural Concrete. American Concrete Institute.

AASHTO (2010). American Association of State Highway and Transportation Officials LRFD Bridge Design Specifications.

Akay B, Karaboga D (2012). A modified artificial bee colony algorithm for real-parameter optimization. *Information Sciences*, 192, 120-142.

Camp C, Akin A (2012). Design of retaining walls using big bang–big crunch optimization. *Journal of Structural Engineering*, 138(3), 438-448.

Das BM (2016). Principles of foundation engineering. Cengage Learning, Eighth Edition.

Deb K (2000). An efficient constraint handling method for genetic algorithms. *Computer Methods in Applied Mechanics and Engineering*, 186 (2-4), 311-338.

Dorigo M, Gambardella LM (1997). Ant colonies for the travelling salesman problem. *Biosystems*, 43(2), 73-81.

Gandomi, AH, Kashani AR, Roke DA, Mousavi M (2015). Optimization of retaining wall design using recent swarm intelligence techniques. *Engineering Structures*, 103, 72-84.

Geem ZW, Kim JH, Loganathan GV (2001). A new heuristic optimization algorithm: harmony search. *Simulation*, 76(2), 60-68.

Goldberg DE (1989). Genetic algorithms and Walsh functions: part I, a gentle introduction. *Complex Systems*, 3 (2), 129-152.

Karaboga D (2005). An idea based on honeybee swarm form numerical optimization, Technical Report TR06, Erciyes University, Turkey.

Karaboga D, Akay B (2011). A modified artificial bee colony (ABC) algorithm for constrained optimization problems. *Applied Soft Computing*, 11(3), 3021-3031.

Kennedy J, Eberhart R (1995). Particle swarm optimization. *Proceedings of ICNN'95-International Conference on Neural Networks*, 1942-1948.

Meyerhof GG (1963). Some recent research on the bearing capacity of foundations. *Canadian Geotechnical Journal*, 1(1), 16–26.

Rajabioun R (2011). Cuckoo optimization algorithm. *Applied Soft Computing*, 11(8), 5508-5518.

Rankine W (1857). Earth Pressure Theory. Phil. Trans. of the Royal Soc.

Sarıbaş A, Erbatur F (1996). Optimization and sensitivity of retaining structures. *Journal of Geotechnical Engineering*, 122(8), 649-656.

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

Uray E, Çarbaş S, Erkan İH, Tan Ö (2019). Parametric investigation for discrete optimal design of a cantilever retaining wall. *Challenge Journal of Structural Mechanics*, 5(3), 108-120.

Yang XS (2009). Firefly algorithms for multimodal optimization. *International Symposium on Stochastic Algorithms*, 169-178.