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Optimization Algorithms in Solving Civil Engineering Problems

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Abstract

Solving problems in different fields is often aimed at optimizing results, which sometimes means minimization and sometimes maximization of answers, and sometimes a combination of both, that is, minimization of some factors such as cost and maximization of others such as quality. The art of obtaining the best result from the model is built based on the conditions and limitations of the problem. Since most of the design optimization problems in construction projects are non-linear and solving them with traditional methods is very difficult and time-consuming, we must necessarily approach the optimal answers through methods such as using existing algorithms. In recent years, many optimization algorithms have been able to pioneer in solving many design problems in various fields of civil engineering and, of course, other scientific branches, and especially in theoretical fields, they have brought many problems closer to the optimal answer. In this article, the use of optimization algorithms and especially meta-heuristic algorithms in solving various problems in various fields of civil engineering, including engineering and construction management, soil and foundation mechanics, structures, water engineering, hydrology and hydraulics, road and transportation engineering, We have discussed transportation and traffic. In some cases, we have briefly described the path to optimize a specific problem and have briefly expressed its results.

Keywords: Optimization algorithms, meta-heuristic algorithms, optimization, civil engineering problems.

1. Introduction

One of the most fundamental challenges facing civil engineers in design and implementation is solving complex problems with multiple answers and determining the answer among the answers. You will see a series of answers before the design engineers consider the field disciplines and apply the viewpoints of the executive engineers to optimize, for example, the depth, diameter, geometric shape, and other components. Sees from different aspects for the desired structural design. This will require a lot of time and money. Optimization algorithms have been able to solve such problems to some extent. Optimization algorithms try to find an acceptable solution according to the constraints and needs of an optimization problem. Optimization algorithms, including heuristic or meta-heuristic algorithms, or sometimes a combination, can provide adequate solutions to the above issues. Optimization algorithms are powerful tools for solving many different problems. These algorithms use a systematic and iterative process to search for the optimal space. Also, for a specific problem, special mathematical techniques can be utilized to ensure that we reach the optimal solution. Because optimization algorithms are prevalent and are used in many issues, they have challenges such as computational complexity, high cost, and the sensitivity of managing constraints. In scientific texts, four steps are usually proposed to solve the problem with optimization algorithms:

A) Formulating the problem: We must first define its general structure to start solving it. This way, all the essential parameters are specified in order, the objectives of the problem are determined, and the input and output parameters are specified. The process's continuation depends on this stage. Therefore, precise and detailed formulation is very effective in solving optimization problems.

B) Modeling the problem: After formulating the problem, it is time to create a mathematical model. Many problems exist, for some of which many formulas have been made. Therefore, we can use predefined models or modify similar models with minor changes to our desired model.

C) Optimization of the problem: In this step, we try to find an optimal or almost optimal solution by applying algorithms to the built model. It is necessary to say that the solution found at this stage is made for the model, and using it in the real world on real problems may lead to finding a different solution.

D) Establishing the problem: In this step, the obtained answer is checked, and the final decision is made regarding the correctness of the created model and the selection of the algorithm. If the obtained answer is acceptable, the optimization work ends here. Otherwise, we must return to the previous steps and repeat the processes.

Choosing an appropriate optimization algorithm can be challenging because different algorithms may find other answers, and their parameter selection requires particular expertise. Therefore, choosing which of the presented algorithms to solve a specific problem has almost no definite answer. Among the things discussed in this article is the use of optimization algorithms in various fields of civil engineering, including structures, in optimizing the dimensions and types of foundations, beam and column sections, retaining walls, trusses, and other structural components. The subject of soil mechanics and geotechnics, investigation of the problem of slope stability, mutual effects of soil layers, influential elements in the design of deep and semi-deep foundations, etc. Pumping and other related issues in this area, in the topic of construction management and project control, which is one of the most challenging areas in civil engineering, especially in terms of cost and time optimization, as well as the design of the most optimal workshop equipment site, Issues related to road and rail transportation include Optimizing urban traffic flow, controlling traffic lights, rationally distributing rail transportation, determining the optimal points for constructing intersections, and other issues related to civil engineers.

2- Application of optimization in civil engineering

2-1- Engineering and construction management

1-1-2- Project control

Time, cost, and quality are the main influential factors in managing and controlling construction projects. All the efforts of the engineers in this field are to manage and coordinate these three parameters, especially the two parameters of time and cost. Appropriate management of funding and allocation of budget and required resources, including workforce, materials, equipment, plans, implementation methods, and other necessary cost items in projects during the duration of the project, permitted and unauthorized delays of the project, extension, and other related issues Project time is the determining factor in successful project management. The quality factor, which depends on time and cost, should not be neglected. Studying the history of many projects shows that excessive and abnormal attention to each of these three vertices has caused deficiencies in the other two factors. In this regard, various researchers have examined the effects of these factors, especially time and cost. Since finding the optimal relationship between these two primary factors could not be obtained from the usual mathematical relationships, they have obtained acceptable results using optimization algorithms. Achieve Using a model based on the Ant Colony Algorithm (ACO)1, Zhang and Thomas minimized the duration and cost of the project simultaneously [1]. Zhuang and Kuang used ACO to solve time and cost trade-off problems [2]. Geem and his colleagues used HSO to minimize project cost and time [3]. Zheng et al. used a GA-based multi-objective

1 Ant Colony Algorithm (ACO)

approach to optimize total time and cost simultaneously [4]. Yang used PSO to solve bi-criteria time and cost analysis [5]. Taheri Amiri and his colleagues have optimized the use of resources by using the weed optimization algorithm (IWO)2 and with intelligent changes in the time of activities, and they claim that by overlapping some activities, they reduce the time and cost of the project and improve the quality of the project. have given [6]. In order to balance time and cost, Hamtian and his colleagues solved a series of sample problems accurately in different dimensions using GAMS3 software. They compared the results with those obtained from the proposed genetic algorithm (GA)4. From the analysis of the obtained results, it appears that the output of the two methods is the same in small dimensions, confirming the proposed algorithm's correctness. Also, the exact solution of some example problems in medium dimensions and all problems of considerable dimensions has not been possible due to the increased complexity. At the same time, the proposed meta-heuristic algorithm has solved these problems, showing the proposed algorithm's power in solving such problems. In addition, the problem of different budget levels has been solved, and the same results have been obtained from two methods for different budget levels. [7]

2-1-2- Project Site design

One of the most essential concerns of implementing construction projects is the optimal location of the facilities and buildings of the project workshop, which is in engineering and construction management issues. Reasonable study efforts have been made in the direction of proper placement and optimization of the construction site, and we will briefly review some of them. Prayugo et al. presented a hybrid algorithm based on symbiotic search (SOS) [5] for solving discrete construction site layout planning problems[8]. Qadiri and his colleagues, during a study in order to increase the safety level of the site, used two firefly meta-heuristic algorithms (FA) and ant colony optimization (ACO) for the Construction Site Layout Problems (CSLP) and compared these two algorithms, the performance (FA) was better. (ACO) has diagnosed [9]. Kaveh and colleagues were able to define an optimal plan for construction site placement (CSLP)[6] by introducing the algorithm (WOA-CBO) from the combination of the Wall Optimization Algorithm (WOA)[7] and the Collision Optimization Algorithm (CBO)[8] [10]. Table 1. shows Temporary and fixed facilities and the associated data and Table 2. Shows the cost of travel between facilities per unit.

Table 1. Temporary and fixed facilities and the associated data.

Index	Temporary and fixed facilities	Length (m)	Width (m)	X coor.	Y coor.
F1	Parking lot	20	20	-	-
F2	Office 1	20	5	-	-
F3	Office 2	20	5	-	-
F4	Office 3	20	5	-	-
F5	Office 4	20	55	-	-
F6	Workshop	5	4	-	-
F7	Storage 1	6	5	-	-
F8	Storage 2	4	5	-	-
F9	Electric generator	2	2	-	-
F10	Toilets	5	6	-	-
F11	Fire station	3	3	-	-
F12	Inflammable materials storage	3	3	-	-
C1	Building	120	95	75	67.5
K1	Tower crane	15	15	75	10
G1	Entrance gate	-	-	155	10

2 invasive weed optimization algorithm (IWO)
3 General algebraic modeling system (GAMS)
4 genetic algorithm (GA)
5 Symbiotic Organisms Search (SOS)
6 Construction Site Layout Planning (CSLP)
7 Wall Optimization Algorithm (WOA)
8 Collision Optimization Algorithm (CBO)

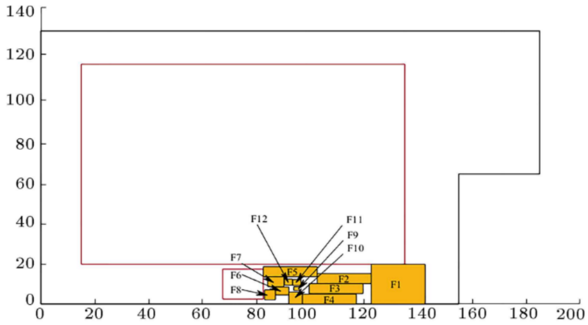
Table 2. Travel cost per unit between facilities

C_{ij}	facility j														
facility i	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	C1	K1	G1
F1	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
F2	4	0	-	-	-	-	-	-	-	-	-	-	-	-	-
F3	4	7.5	0	-	-	-	-	-	-	-	-	-	-	-	-
F4	4	7.5	7.5	0	-	-	-	-	-	-	-	-	-	-	-
F5	4	5.5	5.5	2.5	0	-	-	-	-	-	-	-	-	-	-
F6	1.5	1	1	1	1	0	-	-	-	-	-	-	-	-	-
F7	1.5	1	1	1	1	9.5	0	-	-	-	-	-	-	-	-
F8	1.5	1	1	1	1	9.5	6.5		-	-	-	-	-	-	-
F9	1.5	2	1	3	3	3	3	3	0	-	-	-	-	-	-
F10	1.5	7.5	7.5	7.5	7.5	6.5	6.5	6.5	1	0	-	-	-	-	-
F11	1.5	1	1	1	1	1	1	1	1	1	0	-	-	-	-
F12	1.5	1	1	1	1	3.5	1	1	3.5	1	1	0	-	-	-
C1	1.5	3.5	3.5	3.5	3.5	6.5	4.5	4.5	3.5	3	1	4.5	0	-	-
K1	0	7.5	5.5	7.5	7.5	9.5	9.5	9.5	0	0	1	4.5	5	0	-
G1	1.5	0	0	0	0	3	7*	7*	0	0	0	1	0	0	0

In this study, an attempt has been made to strengthen the original WOA formula to improve the solution's accuracy with collision body optimization (CBO) concepts. The new method, the WOA-CBO algorithm, is applied with reliability and convergence speed to solve the construction site layout planning problem. The appropriate performance of the new optimization algorithm has been demonstrated in three case examples. The first case is a problem of arranging discrete and equal facilities, each of which can be assigned to any place. The second case is the unequal version of the discrete area, with the problem of arranging facilities with more restrictions. Moreover, the last one is a continuous model of construction site plans. In the end, these cases are studied by WOA, CBO, and WOA-CBO, and the results are compared. Based on the results, the third example of this study, which is the most complicated case in choosing the optimal location of the construction site, can be a better criterion for evaluation. In all cases, and especially in the third example, the capabilities and performance of the algorithms have been shown by comparing the statistical results of WOA, CBO, and WOA-CBO after 30 independent periods through 20,000 repetitions with a statistical population size of 200 units, as presented in Table 3. These results show that WOA-CBO has found the lowest cost, and the proposed approach for optimal construction site location is feasible. Moreover, at the end of the study, it was concluded that these algorithms are competitive with other meta-heuristic algorithms and can be used to solve construction site layout problems. Also, Figure 1 shows the lowest cost design obtained, and Figure 2 shows the convergence curves of WOA, CBO, and WOA-CBO for the mentioned example.

Table 3. Results of 30 independent runs for Case 3

Algorithm	Best	Average	Worst	Difference best-average solution%	Difference best-worst solution%	Std. dev
WOA	9049.2	12424	16830	37.29	85.98	2532
CBO	10605	12123	13146	14.31	23.96	351
WOA-CBO	8477.4	10066	12927	18.73	52.48	1380



FFigure 1. The lowest cost layout obtained.

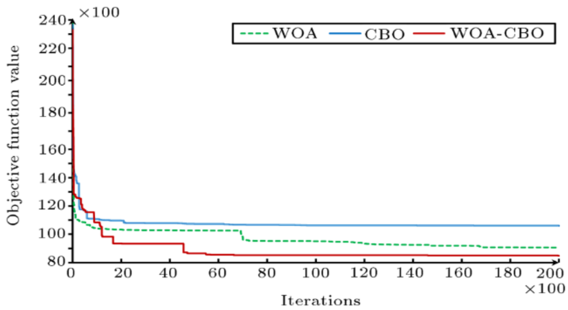


Figure 2. Convergence curves of WOA, CBO, and WOA-CBO for Case 3.

2-2- Soil and foundation mechanics

In soil and foundation mechanics, investigation of slope stability, foundation dimensions, and pile depth are the main activities. For this problem, Gandomi and Kashani have challenged the optimal slope by applying the Particle Swarm Optimization (PSO)[9] algorithm [11]. Gauba, using the ant colony algorithm (ACO), has also investigated the optimal slope in the soil [12]. Moreover, Cheng, in one study using the simulated refrigeration algorithm [13]and once with colleagues, optimized the slope with the Harmony Search (HS) algorithm [14]. In a study on the optimization of pile length and piled foundations, Leung et al. showed that the overall behavior of the foundation can be enhanced by varying the pile length throughout the pile assembly or extended piles [15]. Basha and Bobo investigated a reliability method and a deterministic design method to determine the depth of penetration, anchor tension, and section modulus for the optimal design of the pile wall [16]. To optimize the slope coefficient, Lohar et al. measured the safety factor and other parameters related to stability analysis by optimizing the geotechnical parameters used in slope stability analysis with some meta-heuristic algorithms [17]. In another study, Boomzran reviewed and investigated recent trends in using optimization techniques in geotechnics [18]. Bagheri Sareshki brilliantly conducted research using the MVO[10] multi-initiative algorithm and combining it with the US Federal Highway Administration (FHWA)[11] design method to optimize the construction cost of an earthen wall reinforced with metal reinforcement [19]. Moreover, in the field of investigating the optimal structure based on the number of ground motions, Shaygan and Kardost have been able to compare the performance of several optimization algorithms to find the optimal solution for structure optimization problems and the scaling of ground motions, the mouth-feeding fish (MBF)[12] algorithm from The collision of objects algorithm (CBO) is more efficient and provide an ideal plan to reduce construction costs [20].

2-3-structure

9 Particle Swarm Optimization (PSO)
10 Multi-verse optimization (MVO)
11 Federal Highway Administration (FHWA)
12 mouth-feeding fish (MBF)

2-3-1- Concrete structures

2-3-1-1- The skeleton of concrete buildings

Concrete skeletons have gained more fans today than other types of skeletons for building structures. Therefore, the construction of buildings by optimizing the sections and reinforcements of reinforced concrete (RC)[13] members can significantly help to reduce the construction costs and make the construction more economical; for this reason, researchers use different approaches, especially the approaches based on optimization algorithms have been used. Genetic algorithm (GA)[14] has been widely used in the optimization of RC members such as beams [21] and columns [22]. The harmony search algorithm (HS)[15] is also used in optimal design approaches for continuous beams [23], T-shaped reinforced concrete beams [24], and RC columns [25]. Shaygan et al. have minimized the cost of implementing waffle roofs by using the MBF-CBO optimization algorithm, which combines the MBF and CBO algorithmss [26]. Kaveh and Abadi used HS to design the RC retaining wall [27]. Yang used analytical solutions for passive seismic stresses under earthquake loads with a nonlinear failure criterion [28]. Also, the role of optimization algorithms for the optimal design of reinforced concrete frames to reduce the cost of construction [29-32] and minimize CO2 emissions [22, 33] is noteworthy. In a study, Rozbahan and Jahani propose a new method to optimize the parameters of Tuned Mass Damper (TMD) using mouth-feeding fish (MBF) algorithm based on white noise stimuli. In this research, the effectiveness of optimized TMDs using the proposed method and other methods were compared in reducing the maximum displacement of a ten-story linear structure[34]

2-3-1-2- Reinforced concrete retaining wall

In the design of reinforced walls, optimization algorithms can play a good role in reducing construction costs by optimizing the dimensions of the wall and the amount of aerator used in it. Qadawi and Salavati used the Bacterial Fodder Optimization Algorithm (BFOA)[16] for economic optimization and sensitivity analysis of RC retaining walls [35]. Kaveh et al. used multi-objective GA to optimize the geometry and grading of concrete [36]. Timur and Bektash used learning-based optimization to optimize the dimensions and reinforcement design of RC retaining walls [37]. Also, BB-BC [38] and Charge System Search (CSS)[17] [39]algorithms have been used to optimize RC retaining walls. Yossel et al. have mentioned RC optimization using artificial neural network models [40]. Boshdari and friends used neural networks along with optimization algorithms, including PSO, Archimedes optimization algorithm (AOA)[18], and sparrow search algorithm (SSA)[19], to determine the shear strength of deep reinforced concrete [41]. The study of Shaygan et al. has a powerful and efficient approach to optimizing the construction cost of a reinforced concrete ribbed slab, and it is suggested that this algorithm be used to optimize construction costs. In a targeted study, Shaygan calculated the optimal slab thickness, amount, and spacing of reinforcements in a solid concrete slab by combining the optimization algorithm of mouth-feeding fishes and the optimization algorithm of object collision. In comparison, the results of the optimization of the method above with the results of optimization Through Dicker's optimization algorithms, including the mouth-feeding fish optimization algorithm, particle crowding optimization algorithm, and neural dynamics algorithm, achieved the optimal mouth-feeding fish-object collision algorithm with a powerful and efficient approach [42]

2-3-1-3- Reinforced concrete bridges

Bridgesare one of the most essential concrete structures, and due to the large size and volume of concrete materials and rebar used in them, the optimization of bridges is essential to control their quality and construction cost. An ACO-based method developed by Martínez et al. was compared with GA and a threshold acceptance algorithm for economically optimizing reinforced concrete bridge piers with hollow rectangular sections [43]. This method was also used to design and analyze long reinforced concrete foundations with a height of 90 meters with hollow

13 Reinforced Concrete (RC)
14 Genetic Algorithm (GA)
15 Harmony Search Algorithm (HS)
16 Bacterial Foraging Optimization Algorithm (BFOA)
17 Charge System Search (CSS)
18 Archimedes optimization algorithm (AOA)
19 sparrow search algorithm (SSA)

rectangular sections [44]. Also, Martins et al. studied a method using SA and GA to design reinforced concrete bridge foundations [45]. This study aimed to minimize the cost, the number of reinforcing bars, and the emission of CO2. Dong et al. developed a probabilistic method for pre-earthquake optimization of bridge networks to reduce seismic damage to society, the economy, and the environment [46]. Saad et al. used the Reliability-Based Design Optimization (RBDO)[20] method to improve the life cycle cost formula for better design of concrete bridge structures [47]. Kaveh and friends have conducted a parametric study to investigate the effect of the number of holes on the optimal cost of non-prismatic reinforced concrete box girder bridges, the variables of which were cross-sectional geometry, cone length, concrete strength, and reinforcement of box beams and slabs, which were developed with the advanced vibrating particle system algorithm. (ECBO)[21] were optimized [48].

2-3-2- Steel structures

2-3-2-1- Simple and spatial steel frames

Another primary application of optimization algorithms in civil engineering is the optimal design of various steel structures. Pezeshk et al. used a genetic algorithm (GA) to design two-dimensional, geometric, and nonlinear structures for steel frames [49]. Liu and Yi investigated the life cycle cost for multi-objective design optimization of flexural steel frame structures [50]. Adeli et al. used the two-phase genetic algorithm to measure and optimize the simultaneous topology of steel space frame roof structures [51]. Talat Ahri et al. developed a method using the Eagle strategy (ES) with differential evolution, which was applied to the weight minimization problems of steel frames with discrete variables [52]. In research by Shaygan et al., to scale the acceleration maps from the wavelet transfer, a hybrid meta-heuristic optimization algorithm called (CBO-MBF) was used [53]. With this goal, the wavelet transfer and the algorithm improve the map acceleration, making the response spectrum close to the design spectrum. A gradient-based optimization method for adjusting the hardening-softening behavior of nonlinear mechanical systems was improved by Du and Jansen, and this method was applied to plate frames [54]. Qolizadeh and his colleagues presented a new meta-heuristic Newton algorithm to optimize the design based on the discrete function of steel frames [55]. Greco et al. reviewed ACO and its applications for the constraining analysis of frame-shaped structures; the proposed algorithm was applied to evaluate flat frames' plastic load and failure modes [56].

2-3-2-2- Truss steel structures

Truss systems form the framework of structures such as bridges, towers, roof support structures, etc. Rajeev and Krishnamurthy used discrete variables and a genetic algorithm (GA) with a penalty parameter depending on the constraint violation [57]. Togan and Daluglu went to the modified genetic algorithm to optimize truss structures and used an initial population strategy and grouping of self-consistent members [58]. Perez and Behdinan used PSO to optimize truss structures [59]. Omid-Nesab and Guderzi-Mehr presented a new hybrid algorithm of PSO and GA to obtain the optimal design of truss structures with discrete design variables [60]. ACO is another meta-heuristic algorithm used to optimize truss structures [61]. In research by Shaygan et al., to scale the acceleration maps from the wavelet transfer, a hybrid meta-heuristic optimization algorithm called (Colliding Bodies Optimization - Mouth Brooding Fish (CBO-MBF)) was used. With this goal, the wavelet transfer and the algorithm improve the map acceleration, making the response spectrum close to the design spectrum [53]. In addition, meta-heuristic algorithms such as the firefly algorithm (FA) [62], cuckoo search (CS)22 [63], Bat algorithm (BA)23 [64], and Big Bang Big algorithm (BB-BC)24 [65-67] were also used to design truss structures. Bektash et al. minimized the weight of 3D and 2D truss structures using the Flower Pollination Algorithm (FPA)25 [68]. Toklu et al. proposed a method using HS to obtain the minimum potential energy of truss structural systems [69]. Geometric nonlinear analysis of trusses using PSO was investigated by Taimur et al. [70].

20 Reliability-Based Design Optimization (RBDO)
21 Enhanced Vibrating Particles System (ECBO)
22 cuckoo search (CS)
23 Bat algorithm (BA)
24 Big Bang Big algorithm (BB-BC)
25 Flower Pollination Algorithm (FPA)

2-4- Water engineering, hydrology and hydraulics

In water engineering and projects related to water, hydrology, and hydraulic structures, optimization algorithms have provided significant help to researchers in finding the optimal way to solve problems. Among these issues, we can mention the optimization of water transmission lines, oil and other fluids transmission lines, reducing the costs of hydraulic structure projects, and other cases. Mayer et al. solved water distribution system optimization problems using ACO [71]. Jim et al. used HS to optimally solve standard nonlinear pipe network test problems [72]. Lund and Ferreira used deterministic optimization to develop strategic operating rules for large-scale water resource systems [73]. PSO has also been applied to water distribution system problems [74]. Akbarpour and his colleagues used GA, FA, and PSO algorithms to determine the optimal location of pumping wells in the aquifer [75]. Mugisha identified effective infrastructure optimization through high-impact change management programs and incorporated water loss management strategies [76]. Middleton and Brandt presented an integrated framework that simultaneously considers economic and engineering decisions and optimizes a developed model of CO2 management infrastructure with different carbon prices for the oil sands industry [77]. Haddad et al. used PSO and Pattern Search (PS)[26] to calibrate the groundwater model [78]. Saberi et al. have investigated the performance of CBO meta-heuristic algorithm with FA and GA meta-heuristic algorithms and SOP method in optimizing the operation of Haraz dam reservoir. According to their calculations, CBO algorithm has better results than FA and GA algorithms. and provided the SOP method [79] In another research, Akbarpour et al. used two opposing objective functions to solve the problem of optimizing the exploitation of the studied reservoirs. This research defined the first objective function of minimizing the sum of the second power of the agricultural demand difference from release and the second objective function of maximizing the reliability index. In this study, the parameters of algorithm execution time, the number of solutions located in the Pareto optimal front, and distance, dispersion, convergence, and generational distance criteria were used to compare the investigated algorithms. In this research, the multi-objective version of the particle swarm algorithm (MOPSO)[27] was used along with some new algorithms, which include the multi-objective grasshopper algorithm (MOGA)[28] and the multi-objective ant catcher algorithm (MOALO)[29]. Sistan and Baluchistan provinces were used. The optimization problem was defined with the two objectives of minimizing the sum of the square root of the agricultural demand difference from release and maximizing the reliability index, and the research results showed that all three algorithms can solve this optimization problem. In the meantime, all algorithms were compared according to criteria such as algorithm execution time, the number of solutions located in the optimal Pareto front, distance criteria, dispersion, convergence, and generational distance. This research showed that according to the criterion of algorithm execution time, the MOPSO algorithm showed higher efficiency than other algorithms, with 76.4 seconds.

According to the criterion of the number of solutions located in the optimal Pareto front, the MOALO algorithm with 17 solutions in the first front showed the best performance. According to the distance criterion, the MOGOA algorithm with a value of 0.0131 has shown the best performance among the investigated algorithms. Also, according to the dispersion criterion, the MOALO algorithm outperformed the investigated algorithms with a value of 0.5472. Also, according to the convergence and generation distance criterion, the MOGOA algorithm has shown the best performance among the investigated algorithms with values of 0.0278 and 0.125, respectively. As can be seen, each of the MOALO and MOGOA algorithms has performed better than the others in some criteria. However, the MOALO algorithm has effectively covered the optimal front and, therefore, has created a rich set of optimal solutions. In general, each of the solutions located in the optimal Pareto front represents the parameters defining a command curve for the long-term exploitation of the reservoir. None of these points can be considered generally and absolutely preferable to other answers, but each can be regarded as optimal for the problem in that particular situation, according to specific priorities and limitations. For example, you can choose an option that minimizes the square root of the difference in agricultural demand from release, or in other words, satisfy agricultural demand as much as possible in the entire period, or choose an option that results in the highest reliability. Therefore, it is generally impossible to comment on which solution is the optimal front should be

26 Pattern Search (PS)
27 multi-objective version of the particle swarm algorithm (MOPSO)
28 multi-objective grasshopper algorithm (MOGA)
29 multi-objective ant catcher algorithm (MOALO)

selected. But what is important is that from the total solutions found by the two algorithms, MOALO and MOGOA, a set of solutions that can be a command curve for optimal exploitation of semi-well reservoirs has been obtained [80]

2-5- Road and transportation engineering

Road and transportation, both in the transportation of communication roads, urban and freeways, and rail transportation, have been able to reduce costs and increase quality using optimization algorithms. In this regard, Chakraborty et al. used a Genetic Algorithm (GA) with consideration of transit time to optimize transportation system programs [81]. Also, this algorithm has been employed for urban traffic flow optimization [82], traffic signal coordination problems [83], emergency logistics planning [84], and calibration of rail transport allocation models [85]. Wearing et al. [86] of adaptive reinforcement learning algorithms for learning to control lights. Kuan et al. used GA and ACO to solve the bus feeder network design problem with minimum operator and user costs [87]. ACO was also applied to transportation problems such as vehicle routing [88] and traffic engineering problems [89]. Furthermore, Costa et al. applied SA to the planning of high-speed rail systems [90]. Walraven et al. optimized the traffic flow using a learning-based method [91]. Yu et al. used a technique based on a fuzzy programming approach to optimize signal timing for isolated intersections [92]. Yang et al. optimized the total energy consumption and travel time using a mathematical model to find optimal train movements considering operational interactions [93]. Ebrahimi et al. presented a dual-objective vehicle routing model, including minimizing the imbalance in the travel distances of the used vehicles and the imbalance in the loads assigned to the used cars. Who presented an improved sparse search algorithm to solve the presented model. To investigate the capabilities of the algorithm, they solved various problems. They compared the results with the results obtained from the multi-objective evolutionary algorithm based on differential evolution (MODE)[30] and the multi-objective particle swarm optimization algorithm (MOPSO), which, for example, in most of the indicators It was found that the proposed MOSS algorithm, which is a multi-objective sparse search algorithm, has a higher ability to solve problems than the MODE and MOPSO algorithms. However, in the time index, the proposed algorithm was not preferred. [94]

3- Discussion and conclusion

The most important result that can be obtained at the end of this article is the tremendous impact of optimization algorithms on the ease of optimization of study and executive projects in various fields of civil engineering, including engineering and construction management, soil and foundation mechanics, structures, water engineering, hydrology and hydraulics, road and transportation engineering. It is transportation and traffic. Based on the searches conducted in Google Scholar, we investigated the use of meta-heuristic algorithms by researchers in solving civil engineering problems in the last two decades, the results of which are shown in Figure 3:

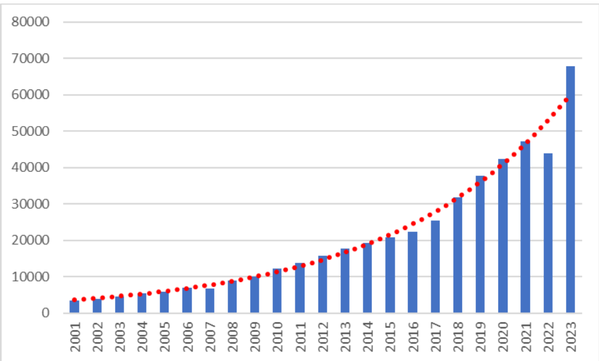


Figure 3. The number of researches conducted on the topic of using optimization algorithms in civil engineering in different years, based on the search in Google Scholar.

30 multi-objective evolutionary algorithm based on differential evolution (MODE)

Mr. Dr. Kaveh and his colleagues [95] in the book "Methodical Optimization Algorithms in Civil Engineering" have analyzed in detail the optimization algorithms used in different branches of civil engineering, which can be the most practical algorithms mentioned by them. It includes the following things that we have checked the frequency of application of these algorithms in civil engineering using the Google Scholar search engine in the time period (2000-2024) and we have displayed their percentage in the diagram of Figure 4.

Golden section search (GSS)

Particle Swarm Optimization (PSO)

Colliding Bodies Optimization (CBO)

Enhanced Colliding Bodies Optimization (ECBO)

Grey Wolf Optimizer (GWO)

Salp Swarm Algorithm (SSA)

Grasshopper optimization algorithm (GOA)

Harmony Search (HS)

Quantum-Inspired Evolutionary algorithm (QEA)

Charged System Search (CSS)

Ant Lion Optimizer (ALO)

Multi-Objective Ant Lion Optimizer (MOALO)

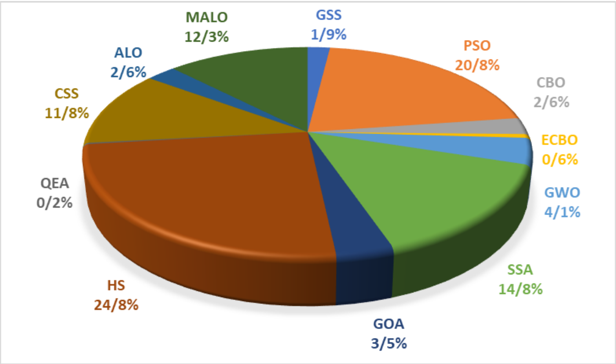


Figure 4. The percentage of algorithms used in civil engineering, based on what Dr. Kaveh and his colleagues have reviewed, between 2000 and 2024.

This article investigates the latest developments regarding optimization and design based on meta-heuristic algorithms in civil engineering. In short, different meta-heuristic algorithms' applications, including genetic algorithms, bat algorithms, harmony search, ant colony optimization, cuckoo search, firefly algorithm, particle swarm optimization, simulated refrigeration, etc., are presented in the optimization of various research and operational projects. All this can be considered a timely illustration of the vast and expanding literature on design optimization in civil engineering. The variety of optimization algorithms and their usage methods show the flexibility and efficiency of these algorithms. Determining the proposed algorithm in each problem of the set of civil engineering problems requires a detailed study of that problem and the need for an optimal path in each issue. Using a specific type of algorithm also requires a better understanding of optimization algorithms, considering the diversity and effectiveness of each algorithm. At the end, the amount of use of different optimization algorithms based on the frequency of each algorithm and its field of application is given in Table No. 4. As can be seen, civil engineers have used GA, ACO, PSO, and HS algorithms more frequently than other algorithms in optimizing civil engineering problems.

Table 3. The frequency of each algorithm in different applied fields of civil engineering

Algorithm	frequency	The field of use	References
GA	30	concrete bridge	[43]
		concrete bridge	[44]
		CSLP	[18]
		hydraulics, hydrology	[79]
		Project Control	[4]
		Project Control	[7]
		CSLP	[17]
		Concrete buildings	[21]
		Concrete buildings	[22]
		Concrete buildings	[28]
		Concrete buildings	[30]
		Concrete buildings	[32]
		Concrete wall	[36]
		concrete bridge	[45]
		Steel frames	[49]
		Steel frames	[50]
		Steel frames	[51]
		Steel frames	[54]
		Trussed steel	[57]
		hydraulics, hydrology	[76]
		hydraulics, hydrology	[77]
		transportation	[81]
		transportation	[82]
		transportation	[83]
		transportation	[84]
		transportation	[85]
		transportation	[87]
		hydraulics, hydrology	[75]
		Trussed steel	[60]
		concrete bridge	[46]
ACO	14	Project Control	[1]
		Project Control	[2]
		CSLP	[12]
		Steel frames	[56]
		Trussed steel	[61]
		hydraulics, hydrology	[71]
		transportation	[88]
		transportation	[89]
		concrete bridge	[43]
		concrete bridge	[44]
		CSLP	[9]
		CSLP	[18]
		Concrete buildings	[29]
		transportation	[87]

Algorithm	frequency	The field of use	References
PSO	13	CSLP	[18]
		Concrete buildings	[29]
		CSLP	[16]
		hydraulics, hydrology	[75]
		Project Control	[5]
		CSLP	[11]
		Trussed steel	[59]
		Trussed steel	[70]
		hydraulics, hydrology	[73]
		hydraulics, hydrology	[74]
		hydraulics, hydrology	[78]
		Concrete wall	[41]
		Trussed steel	[60]
HS	10	Concrete buildings	[29]
		CSLP	[15]
		Trussed steel	[69]
		hydraulics, hydrology	[72]
		Project Control	[3]
		CSLP	[14]
		Concrete buildings	[23]
		Concrete buildings	[24]
		Concrete buildings	[25]
		Concrete buildings	[27]
BB-BC	5	Concrete wall	[38]
		Trussed steel	[65]
		Trussed steel	[66]
		Trussed steel	[67]
		Concrete buildings	[29]
FA	4	CSLP	[9]
		hydraulics, hydrology	[79]
		Trussed steel	[62]
		hydraulics, hydrology	[75]
MBF	4	Concrete buildings	[34]
		Concrete wall	[42]
		Concrete buildings	[26]
		CSLP	[20]
SA	4	transportation	[90]
		CSLP	[14]
		Concrete buildings	[33]
		concrete bridge	[46]
CBO	3	hydraulics, hydrology	[79]
		CSLP	[20]
		Concrete buildings	[26]
MODE	2	transportation	[94]
		transportation	[94]
TLBO	2	Concrete wall	[37]
		transportation	[91]

Algorithm	frequency	The field of use	References
ABC	1	CSLP	[18]
ANNA	1	Concrete wall	[40]
AOA	1	Concrete wall	[41]
BA	1	Trussed steel	[64]
BFOA	1	Concrete wall	[35]
BOA	1	CSLP	[16]
CBO-MBF	1	Steel frames	[53]
CSA	1	Trussed steel	[63]
CSS	1	Concrete wall	[39]
DE	1	CSLP	[16]
ECBO	1	concrete bridge	[48]
ES-DE	1	Steel frames	[52]
FMO	1	transportation	[92]
FPA	1	Trussed steel	[68]
IWO	1	Project Control	[6]
MGA	1	Trussed steel	[58]
MO	1	transportation	[93]
MOALO	1	hydraulics, hydrology	[80]
MOGOA	1	hydraulics, hydrology	[80]
MOPSO	1	hydraulics, hydrology	[80]
MOSA	1	Concrete buildings	[31]
MVO	1	CSLP	[19]
NMA	1	Steel frames	[55]
RBDO	1	concrete bridge	[47]
RLA	1	transportation	[86]
SCA	1	CSLP	[16]
SOS	1	CSLP	[8]
SSA	1	Concrete wall	[41]
WOA-CBO	1	CSLP	[10]

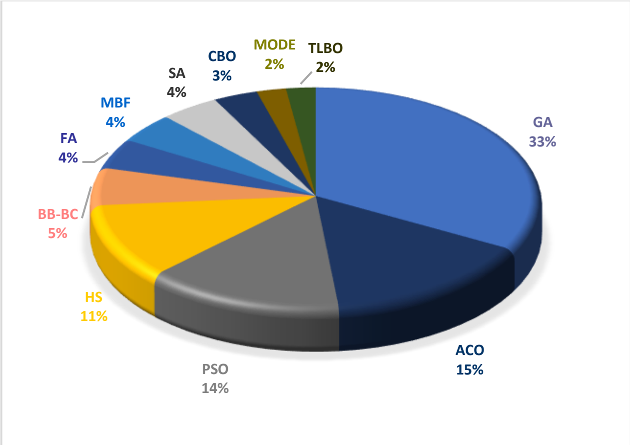


Figure 5. Percentage of use of optimization algorithms in civil engineering.

The frequency of using optimization algorithms in civil engineering for more than one case in the statistical collection mentioned in this article is shown in 3-D Pie diagram in figure 5.

According to the results of the search for articles that deal with the above widely used optimization algorithms in the Google Scholar search engine, it provided reliable results that are briefly shown in the following diagram:

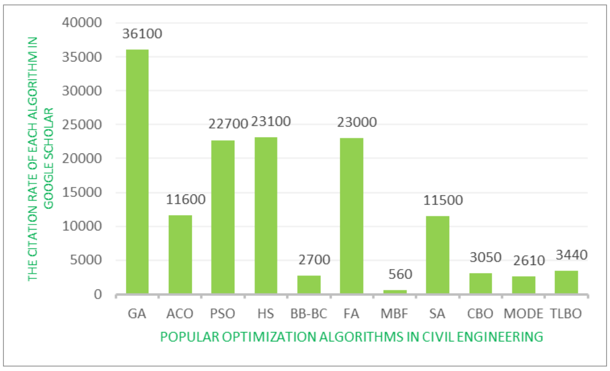


Figure 6. The amount of use of selected optimization algorithms in solving civil engineering problems based on the search in G. Gol Skolar between the years 2001 and 2023. The search date is February 26, 2024.

Now, by sorting the above diagram, you can reach the final diagram below, which is sorted based on the most references to the least references:

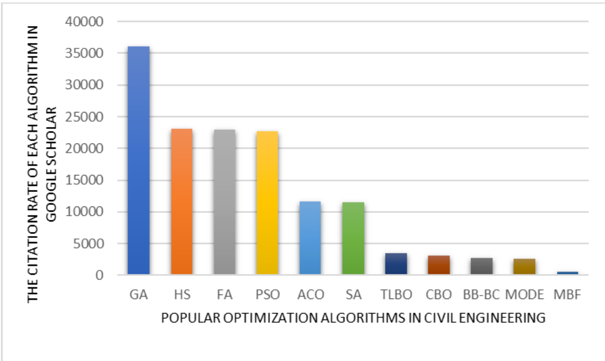


Figure 7. The amount of use of selected optimization algorithms in solving civil engineering problems in a sorted form, based on the search in Google Scholar between the years 2001 and 2023. Search date February 26, 2024

Since the year of presentation of the algorithms is different, direct comparison of their references does not seem reasonable, therefore, by weighting the above algorithms, we compare their use more precisely:

Table No. 4 shows a list of reviewed algorithms by considering the year of presentation and the life period of each algorithm, after weighting the number of references made by considering the life weight of each algorithm, we reach Table 5, which is The table of references of each algorithm is arranged according to the weighting done and they are arranged in the order of the most to the least references.

Table 4. Weighting of the use of meta-heuristic algorithms in civil engineering

Algorithm	frequency	Birth Year	Age	Weight	frequency According to Weithing
GA	30	1975	49	1/00	30
ACO	14	2006	18	0/37	38
PSO	13	1995	29	0/59	22
HS	10	2001	23	0/47	21
BB-BC	5	2006	18	0/37	14
FA	4	2007	17	0/35	12
MBF	4	2007	17	0/35	12
SA	4	1983	41	0/84	5
CBO	3	2009	15	0/31	10
MODE	2	2010	14	0/29	7
TLBO	2	2011	13	0/27	8
ABC	1	2005	19	0/39	3
ANNA	1	2016	8	0/16	6
AOA	1	2021	3	0/06	16
BA	1	2010	14	0/29	4
BFOA	1	2008	16	0/33	3
BOA	1	2018	6	0/12	8
CBO-MBF	1	2021	3	0/06	16
CSA	1	2016	8	0/16	6
CSS	1	2017	7	0/14	7
DE	1	1995	29	0/59	2
ECBO	1	2020	4	0/08	12
ES-DE	1	2014	10	0/20	5
FMO	1	2012	12	0/24	4
FPA	1	2008	16	0/33	3
IWO	1	2006	18	0/37	3
MGA	1	2005	19	0/39	3
MO	1	2021	3	0/06	16
MOALO	1	2016	8	0/16	6
MOGOA	1	2015	9	0/18	5
MOPSO	1	2011	13	0/27	4
MOSA	1	2017	7	0/14	7
MVO	1	2017	7	0/14	7
NMA	1	2018	6	0/12	8
RBDO	1	2021	3	0/06	16
RLA	1	2016	8	0/16	6
SCA	1	2016	8	0/16	6
SOS	1	2016	8	0/16	6
SSA	1	2019	5	0/10	10
WOA-CBO	1	2018	6	0/12	8

Table 5. The rate of use of meta-heuristic algorithms in civil engineering based on their age weight

Algorithm	frequency According to Weithing
ACO	38
GA	30
PSO	22
HS	21
AOA	16
CBO-MBF	16
MO	16
RBDO	16
BB-BC	14
ECBO	12
FA	12
MBF	12
CBO	10
SSA	10
BOA	8
NMA	8
WOA-CBO	8
TLBO	8
MODE	7
CSS	7
MOSA	7
MVO	7
ANNA	6
CSA	6
MOALO	6
RLA	6
SCA	6
SOS	6
MOGOA	5
ES-DE	5
SA	5
FMO	4
MOPSO	4
BA	4
BFOA	3
FPA	3
IWO	3
ABC	3
MGA	3
DE	2

Figure 8 shows the amount of use of selected optimization algorithms in solving civil engineering problems according to the weight given in table 4, based on the search in Google Scholar between 2001 and 2023 until the search date of February 26, 2024.

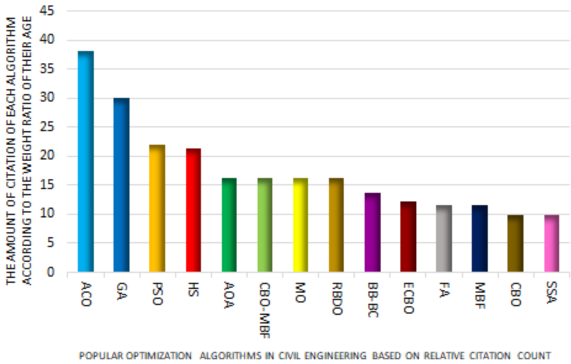


Figure 8. The amount of use of selected optimization algorithms in solving civil engineering problems based on the weight ratio of their ages

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