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Metaheuristics in civil engineering: A review

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Abstract. Real-world engineering problems deal with nonlinear, nonconvex, and discontinuous solution space. Due to the high level of complexity, state-of-art methods are required for handling this sort of NP-hard type problem. One of the most efficient strategies is considering metaheuristic optimization algorithms to facilitate them. Civil engineering problems because of the high level of uncertainties and effective parameters have been the subject of many optimization-based studies. In this paper, the main effort was to provide an overview of different applications of optimization algorithms for civil engineering problems. Moreover, we classified a large number of available studies on the implementation of metaheuristics in various fields of civil engineering classified in this study and highlighted the most important features of them to provide an efficient reference for active researchers in this field.

Keywords: engineering optimization; civil engineering; global optimization; metaheuristic algorithms

1. Introduction

Engineering problems can be broadly categorized into two major approaches: 1- analysis, 2- design. Solving this sort of problem found to be a very challenging and complicated task. However, soft computing-based techniques, including fuzzy logic, neural network, and evolutionary computation, have been proved to be advantageous and sophisticated methods for facilitating this purpose (Singh and Ruparathna 2020, Akhani *et al*. 2019, Azizi *et al*. 2017). Robust design optimization has extensively been studied in different fields of engineering. To this end, the intended problem must be defined mathematically in the form of an objective function. Then, this objective function would be the subject of either minimization or maximization. Generally, engineering problems are complicated because of dealing with a large number of design variables and many limitations as constraints. Although optimization algorithms are capable of solving those problems, their level of success is related to the level of complexity of the tackled problem. Hence, finding an appropriate algorithm to handle a given problem considered to be a

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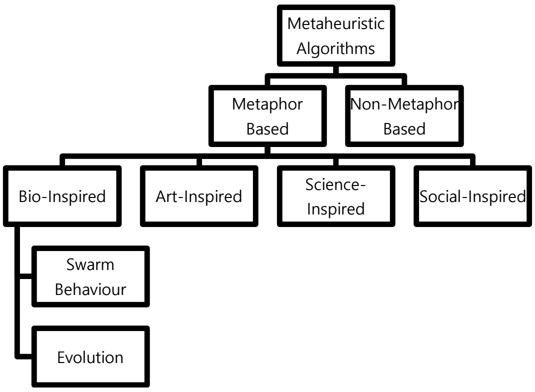

Fig. 1 Classification of metaheuristic algorithms

difficult challenge during the past few decades. Therefore, in addition to finding new applications of optimization algorithms, many researchers attempted to find the best tools for handling a specific problem. Due to the complex nature of civil engineering problems, such efforts have been made in different sub-fields such as structural engineering (Yang *et al*. 2016a, Gandomi *et al*. 2013b), geotechnical engineering (Yang *et al*. 2012, Kashani *et al*. 2016, Sanaeirad and Kashani 2016, Hajihassani *et al*. 2018), transportation (Yang *et al*. 2016a), and water resource engineering (Yang *et al*. 2016a).

Mathematical optimization is finding the best solution within a set of allowable potential alternatives for a specific problem. Optimization algorithms can be divided into deterministic and stochastic. Deterministic approaches encountered many difficulties and limitations to approach real-world optimization problems. On the other hand, stochastic optimization algorithms and, in particular, metaheuristic algorithms found to be very efficient in dealing with highly complex problems. Roughly speaking, metaheuristics are algorithms that apply to a wide range of problems with only minor modifications. These algorithms work based on two main phases: diversification and intensification. Hence, a good balance between them would result in an acceptable performance. As an essential feature of every metaheuristic algorithm is that there is no guarantee that the final solution is the best choice for the tackled problem. Many researchers address this concern by developing new algorithms or improving the existing methods (Gandomi 2012, Gandomi 2014, Mirjalili *et al*. 2017, Gandomi and Kashani 2016, Gandomi and Kashani 2018b). Metaheuristic optimization algorithms can be categorized into non-metaphor-based and metaphor-based algorithms as shown in Fig. 1. Metaphor-based algorithms are including bio-inspired (swarm and evolutionary algorithms), art-inspired, science-inspired, social inspired.

Nowadays, by developing new optimization algorithms, the research papers on the basis of engineering optimization are extensive. Among them, civil engineering was prone to much attention from optimization researchers because of a very complex nature. Despite plenty of literature, there is not enough review study to classify and collect available publications in this area. In this review paper, we provide an extensive survey on different applications of metaheuristic algorithms to civil engineering problems. To this end, we addressed the following purposes: 1- collecting and categorizing a comprehensive list of references with relevant background to the civil engineering optimization; 2- finding and introducing the most up to dated methods and problems in the area of civil engineering optimization; 3- present current challenges in this field, some critiques, and future targets.

2. Metaheuristic optimization algorithms

Metaheuristic algorithms are realized to be a crucial part of modern optimization. Metaheuristic is the word proposed by Glover (1986). It expresses more independence from characteristics of the tackled problem than heuristics. Basically, metaheuristic algorithms converge to the global solution as much as possible instead of finding the exact solution using two main strategies: exploration and exploitation. The former pushes the algorithms to go beyond the current search area and prevent it from converging to a premature solution. At the same time, the latter searches for the best solution area to evade from the local optimal solutions. A proper trade-off between those features is necessary for an efficient search process.

Metaheuristics are stochastic optimization methods derived from natural phenomena such as sociology, physics, mathematics, art, politics, etc. From a different perspective, a wide variety of categorizations are proposed for those algorithms. Osman (2003) classified metaheuristics into three groups: local search, construction-based, and population-based. Gendreau and Potvin (2005) categorized them into trajectory-based and population-based algorithms. Fister *et al*. (2013) proposed two main clusters of non-nature inspired and nature-inspired. A large number of metaheuristic algorithms can be found in literature, though we explained some of the most well-known methods briefly in the following.

Genetic algorithm (GA) is one of the most popular evolutionary algorithms inspired by the Darwinian theory of natural selection (Holland 1975). The essence of GA was fundamental to many modern evolutionary-based algorithms. GA encodes the potential solutions in the form of a chromosome of genes. Every chromosome represents a possible solution as an array of design variables. GA starts with a population of chromosomes and manipulates them based on biological evolutions (i.e., crossover, recombination, mutation, and selection) to generate a new population. The quality of individuals is directly related to the objective value. GA uses an iterative based approach to reach the fittest population using the mentioned operators.

Particle swarm optimization (PSO) is another metaheuristic algorithm developed by Kennedy and Eberhart (1995). PSO imitates the social behavior of a school of birds in searching for foods. In fact, this algorithm starts with an initial random population and moves the particles within the solution space by considering a quality called velocity. The velocity term is determined by the content of the best particle and the best experience of each particle. Therefore, in opposite to GA, instead of generating new particles, PSO modifies the position of current individuals to find the best solution.

Simulated annealing (SA) is developed by Kirkpatrick *et al*. (1983) based on the metal annealing process. The most robust feature of SA is its ability to evade local minima. Therefore, this algorithm has been an excellent choice to strengthen the local search ability of different metaheuristic algorithms via hybridization. In fact, SA defines an initial temperature for metal and follows a cooling pattern to reach a specific temperature. The mentioned cooling pattern is used to calculate a probability for accepting a series of changes to the current solutions. Continuing this strategy will end up with the final solution.

Harmony search (HS) is a music-inspired algorithm introduced by Geem *et al*. (2001). Hs inspired by the improvisation of musicians through variation resulting in aesthetic harmony. Improvisation can be fulfilled through three main strategies: 1- play any famous piece of music (using a memorized pitches); 2- play something similar to a known piece (adjusting the pitch slightly); or 3- compose a new note. Therefore, HS simulates those three steps to generate new solutions and solve the tackled problem.

There are many other optimization algorithms, and obviously, many more would be developed in the future. Therefore, it is necessary to study the basic rules governing the optimization procedure before considering them as a solver for a given problem.

3. Civil engineering optimization

This section is devoted to the comprehensive review of different applications of optimization algorithms for civil engineering problems. To this end, we divided all the publications into three sub-categories: 1- structural engineering, 2- geotechnical engineering, and 3- transportation, hydraulic and hydrology, and construction management engineering.

3.1 Structural engineering

3.1.1 Truss optimization

Optimum design of truss structures is one of the most critical and challenging tasks in civil engineering. To now, many researchers attempted to study different aspects of truss structures designing through weight minimization. To be more precise, this problem has been handled by considering size, shape, and topology optimization. Several design procedures were deemed to be based on stresses, slenderness ratios, deflections in the members, or natural frequency of the structure. Finding the most efficient tool for handling this challenge has been continued in numerous studies.

Capriles *et al*. (2007) utilized a variation of ant colony optimization algorithm (ACO), named rank-based ant system (RBAS), to handle weight minimization of truss structures using discrete design variables. They considered stress, displacement, and buckling as criteria to control the design procedure.

Artificial bee colony (ABC) was tackled by Sonmez (2011) for handling the minimum weight design of truss structures using discrete design variables. The design constraints were established based on stress, buckling, and nodal displacement. The obtained results proved that ABC was successful in all cases. Although, in terms of the number of analyses, ABC could not outperform other similar studies, it was much faster than other methods concerning CPU time.

Sadollah *et al*. (2012) employed a mine blast algorithm (MBA) to solve truss optimization. MBA illustrated an acceptable performance thanks to its fast convergence and low computational cost. Miguel and Miguel (2012) took multiple natural frequencies into account for optimum shape and size design of truss structures. They used the harmony search (HS) and the firefly algorithm (FA) to handle this problem. The same number of analysis were considered for both of those algorithms. Based on the results, HS found the solutions in a shorter time, though FA was capable of finding more optimal designs.

Gandomi *et al*. (2013a) engaged the cuckoo search (CS) algorithm for handling truss optimization. CS was in superiority compared to the following algorithms: GA, PSO, HS, SA, sequential linear programming (SLP), augmented Lagrangian (AL), geometrical programming (GP), and centre points (CP). A multi-stage PSO (MSPSO) was used for truss problem in a study conducted by Talatahari *et al*. (2013b). The efficiency of this modified algorithm was approved based on the results on several benchmark problems. Baghlani and Makiabadi (2013) also inspected optimum truss size and shape design subject to frequency constraints. Teaching-learning-based optimization (TLBO) was selected to deal with this problem. TLBO successfully proposed lower weight designs rather than previously utilized metaheuristics in similar numerical simulations.

In 2015, more challenging truss optimization was handled by Kaveh and Mahdavi (2015) by considering the size and topology optimization. They considered colliding body optimization (CBO) for solving four numerical case studies. CBO obtained better results compared to previously used algorithms such as GA, FA, and CSS for all the case studies Concalves *et al*. (2015) used search group algorithms (SGA) for size, shape and topology optimization of truss structures using discrete design variables. The major design criteria were stress, slenderness, displacement, and natural frequency. The authors claimed that SGA found the best ever solutions in their selected case studies at that time. Sadollah *et al*. (2015) applied water cycle algorithms (WCA) and improved MBA (IMBA) for discrete sizing optimization of truss structures based on natural frequency considerations. The simulations of four case studies demonstrated the superiority of IMBA over MBA and WCA algorithms in large scale truss structures. Bekdas *et al*. (2015) concentrated on size optimization of truss structures using flower pollination algorithm (FPA). The results proved to be competitive with other previously tackled algorithms.

Kazemzadeh Azad (2017) proposed guided and guided hybrid versions of ADS, MBB-BC, and EBB-BC for handling truss optimization based on the American Institute of Steel Construction-Load and Resistance Factor Design (AISC-LRFD) regulations. In this study, guided hybrid method of ADS and EBB-BC named (GADS-EBB) proved to be the best algorithm among the proposed techniques. Kazemzadeh Azad (2018) explored the effect of seeding an initial population to three following metaheuristic algorithms for solving truss structure: ADS, modified BB-BC (MBB-BC), and exponential BB-BC (EBB-BC). In this way, the initial population was fed in three different ways: 1- random initial population, 2- feasible generated solutions with the largest cross-sectional area of the members, and 3- highest feasible solution resulted from assigning each available cross-section to all the elements. The results confirmed that seeding an initial population can be resulted in decreasing the infeasibility of the solutions quickly in the very first steps.

Tejani *et al*. (2018) incorporated mutation-based modifications into the following optimization algorithms: teaching-learning-based optimization (TLBO), heat transfer search (HTS), water wave optimization (WWO), and passive vehicle search (PVS). Five benchmark problems were the subject of this study based on satisfying stresses, displacement, and kinematic stability. The results showed the positive impact of the mutation on the enhancement of optimization algorithms. Kaveh and Zakian (2018) employed an improved grey wolf optimizer (IGWO) for minimum weight design of truss structures. The proposed modification improved the performance of CBO in handling the problems.

Bekdas *et al*. (2019) utilized black-box type, total potential optimization using metaheuristic algorithms (TPO/MAs). They considered four different hybrid algorithms (Jaya algorithm (JA) with Levy flight (JALD), JALD with linear distribution (JA2LD), JA with consequent student phase (JA2SP), and JA with probabilistic student phase (JA1SP)) in their research. Five benchmark problems were enlisted for evaluating different methods and their results compared to similar studies.

3.1.2 Frame optimization

Optimum design of steel frame structures is a challenging task in civil engineering because of dealing with a large number of design variables and constraints. Due to the massive amount of materials required for constructing a given frame, any effort in decreasing the steel weight may cause saving a considerable amount of budget in every project. Thanks to metaheuristics, this complex task has been handled effectively during the past few decades. In the following, a review of different endeavors on this basis is collected.

Hasancebi *et al*. (2010a) utilized the ADS algorithm to handle discrete optimization of steel frames. They followed American Institute of Steel Construction -Allowable Strength Design (AISC- ASD) code to form the design procedure. Their proposed methodology was assessed through two numerical case studies. A combination of gravity and lateral loads due to wind loads was applied to the structures. The obtained results were compared to the original HS algorithm as well as other previously utilized algorithms in the same case studies. It was stated that ADS outperform HS's results significantly.

Kazemzadeh Azad *et al*. (2013) utilized an upper strategy for the optimum design of steel frames by metaheuristic algorithms. To that end, they employed the BB-BC algorithm and its two improved versions (MBB-BC and EBB-BC). The main objective of using this scheme is eliminating unnecessary analyses within the optimization process. In this study, AISC-LRFD regulations governed the design procedure. Validation of the proposed methodology was inspected through two numerical case studies. The proposed approach resulted in decreasing the structural analyses for 135-member structure by 94.97%, 89.75%, and 92.94% for the UBB–BC, UMBB–BC, and UEBB–BC algorithms, respectively. Moreover, those numbers for 1026-member were 95.72%, 94.1%, and 97.1%, respectively. Therefore, the proposed strategy was proved to be efficient in computationally expensive problems without affecting the exploration and exploitation of the optimization algorithms.

Talatahari *et al*. (2013a) employed accelerated PSO (APSO) for optimum design of frame structures based on AISC-LRFD requirements. Two numerical simulations were established on a one-bay eight-story frame and three-bay 15-story frame. Both the frames were supposed to tolerate vertical and horizontal loads. The results showed that APSO performed equivalent to or better than some other utilized algorithms in similar studies.

Hasancebi and Carbas (2014) selected the BAT algorithm for the size optimization of steel frames based on AISC-ASD. Three case studies, including a 132-member unbraced frame, a 209-member industrial building, and an 1860-member high-rise braced frame, were investigated in this study. A comparison of the results in this study with other previous efforts proved the efficiency of their tackled algorithm for handling frame optimization problem.

Kaveh and Farhoudi (2015) utilized DE and dolphins echolocation optimization (DEO) for layout optimization of braces in steel frames. The design procedure was based on AISC. The results from three case study simulations were compared to GA, ACO, PSO, and BB-BC that declared the superiority of DE and DEO in handling the tackled problems. Gholizadeh and Poorhoseini (2015) applied modified DEO (MDEO) for the optimization of steel frames. This modified algorithm was based on using one-dimensional Gauss chaotic maps for determining the step locations. The design procedure was based on AISC-ASD. The performance of the proposed algorithm was examined through a comparison with some other algorithms applied to the same numerical examples previously. The result approved the better performance of MDEO thanks to finding lighter designs.

Daloglu *et al*. (2016) dealt with the problem of steel frame optimization by taking soil-structure interaction into account. They fulfilled the analysis of the structures using SAP2000 based on AISC- LRFD regulations. GA and HS were selected to handle the optimization procedure. Results demonstrated that considering the soil-structure interaction caused heavier designs, especially due to stronger columns. More elastic soils resulted in heavier designs. Lateral displacement of the structure, as well as the inter-story drift, were critical constraints within the design procedure. Aydogdu *et al*. (2016) proposed a coupled ABC and levy-flight distribution (LFABC) for handling steel space frame. AISC- LRFD requirements governed the optimum design procedure. LFABC obtained better solutions compared with ABC, dynamic HS, and ACO with lighter weights and faster convergence rate.

Bybordiani and Kazemzadeh Azad (2019) investigated the optimum design of steel braced framed with dynamic soil-structure interaction. Typical steel frames were considered resting on a rigid base as well as half-space. The standard massless foundation was used to model the unbounded soil domain. The seismic time-history analysis was applied to the model based on two sets of ground motions.BB-BC algorithm was selected to handle the optimization problem. Two 5-story and 10-story frames were considered for the numerical simulations.

3.1.3 Miscellaneous structural optimization

Complex nature of civil engineering problems enticed many researchers to find different application of optimization algorithms in this field for the sake of facilitating them as much as possible. Structural and earthquake engineering problems as a sub-field of civil engineering attracted many attentions in this regard. Some of those applications are summarized in the following. In addition to the mentioned structures in sections 3.1.1 and 3.1.2, other large-scale real-world structures and structural elements themselves were tackled for optimization tasks.

Gholizadeh and Shahrezaei (2015) dealt with optimal placement of steel plate shear walls for a frame using BAT algorithm. Two main objectives were followed in their study as 1- size optimization of frames with two fixed layout of shear walls, 2- finding the optimum layout of shear walls. The objective function was developed based on minimization of weight of the structure as a function of cross section of structural elements and web plate thickness for each shear wall. The results showed that optimal placement of shear walls resulted in lighter designs rather than fixed layout. Moreover, the results indicated that the BAT algorithm performed better than GA and PSO in this study.

Optimum design of steel plate shear wall was selected for further investigations by Kaveh and Farhadmanesh (2019). They considered PSO, CBO and ECBO for handling this problem. Steel plate shear wall was modelled using strip model for low seismic loads and for the performance-based optimization with high seismic loads. Numerical case studies revealed that CBO handled shear wall problem efficiently while ECBO outperformed other algorithms in this study. Moreover, steel shear walls resulted in lighter weights of structure than other lateral load resisting systems. Performance-based design results demonstrated that top panels in a frame required thicker web plates in case of defining minimum weight and drift uniformity as two separate objective functions.

In an effort by Zavala *et al*. (2016) two cable-stayed bridges were selected for optimization through seven multi-objective approaches. In this study different parts of a bridge including columns, anchored cables, link beam of the columns, transversal beams, longitudinal beams and stayed cables were defined as variables with specific cross-sectional shape (circular cable, I-beam, and hollow rectangle). Two objective functions were determined as total weight of the structure and aggregated nodal displacements. The following multi-objective algorithms were utilized for handling this problem: 1- non-dominated sorting genetic algorithm-II (NSGA-II), 2- pareto archive evolution strategy (PAES), 3- multi-objective cellular genetic algorithm (MOCell), 4- S metric selection evolutionary multi-objective algorithm (SMS-EMOA), 5- multi-objective evolutionary algorithm based on decomposition (MOEA/D), 6- speed-constrained multi-objective PSO algorithm (SMPSO), and 7- generalized differential evolution algorithm (GDE). Different aspects of these algorithms and their results were discussed in this study and their cons and pros were highlighted.

Optimization of a three-span bridge as well as a 26-story 942-bar truss tower were explored in a study by Cao *et al*. (2018). The minimum weight of those structures was the main concern in this effort. To do that, an approach based on using a filter strategy was combined with five different algorithms (PSO, HS, CS, TLBO, and FPA) for running the optimization process. The proposed methodology aimed to eliminate unnecessary fixability checks for the given solution during the optimization procedure to improve computational efficiency. The results confirmed significant improvement of the computational efficiency.

Temur *et al*. (2014) studied optimization of cable structures using TPO/MA method and HS optimization algorithms. Designing procedure was based on the total potential energy principle. This method was evaluated by solving two cases: 1- flat cable net one by one and 2- flat cable net two by two. Bekdas and Nigdeli (2016) studied reinforced concrete columns optimization using TLBO algorithm. The design procedure minimized the final cost as a function of web width, height, longitudinal and shear reinforcements. To this end, American concrete institute (ACI 318) requirements for strength and slenderness were considered. The obtained results by TLBO compared with BAT and HS algorithms in order to evaluate its suitability and efficiency.

Sánchez-Olivares and Tomas (2017) accounted the minimum cost design of reinforced concrete rectangular sections under compression and biaxial bending using GA, FA and modified FA (MFA) optimization methods. ACI 318 was supposed to control the design procedure. The design variables were the depth of neutral axis, the angle of neutral fiber, width and height of the section, bar size and numbers at the left, right, top and bottom sides of the section. The proposed MFA performed better than GA and original FA on this case study.

Bekdas (2019) tackled metaheuristic-based optimization of post-tensioned axially symmetric cylindrical walls. Several algorithms were selected for this research including FPA, TLBO, and JA. Moreover, some hybrid approaches developed based on combining JA and Levy flights, JA and Levy flights with probabilistic student phase (JALS), JA and Levy flights with consequent student phase (JALS2), and JA with probabilistic student phase. The objective function was defined as the total construction cost resulted from concrete volume, total weight of steel reinforcements, weight of post-tensioned cables, and total surface area. The results revealed that JALS2 and JALS were the most effective algorithms in this study.

Gholizadeh and Aligholizadeh (2013) considered optimum cost design of reinforced concrete frames using BAT algorithm based on ACI 318 requirements. The effective factors in the final cost were geometry of beams and columns, and length and area of steel rebars. Three case studies including four, eight and twelve story frames affected by dead, live and earthquake loads were subject of this study. Comparison of BAT algorithm's results with other available studies demonstrated the considerable superiority of this algorithms over other techniques.

Hasancebi *et al*. (2010b) solved the geodesic steel domes optimization problem based on AISC-ASD using different algorithms. In this study, minimum weight of the structure was the main objective. Optimization procedure was handled using SA, ES, PSO, HS, TS, ACO, and SGA. Numerical simulations of a 130-member pin-jointed geodesic steel dome indicated that ES, SA, and PSO reflected more reliable convergence than other algorithms.

Kamyab Moghadas *et al*. (2013) dealt with optimization of geometrically nonlinear double-layer domes using FA algorithm. The structure was analysed for both linear and non-linear responses of structure using ANSYS software. The height along with the circumferential ring varied parabolic or sinusoidal. Objective function defined as the weight of structure based on cross-sectional area, length and density of elements. Numerical simulations demonstrated that nonlinearly designed structures are considerably lighter than linear ones.

Kaveh and Sabeti (2018) studied optimum design of jacket supporting structure for offshore wind turbines using CBO algorithm. To this end, total weight of structure supposed to be the objective function and diameter and thickness of 10 groups of elements took part in the optimization procedure as design variables. The effective loads on the structure resulted from dead loading, wind loading, and wave loading. The proposed model was validated using a numerical case study in the presence of hydrodynamic and aerodynamic loadings. Health monitoring and damage detection are other hot debates in the field of civil engineering which deals with complex problems. Optimization algorithms found to be efficient in handling those problems to some extent.

3.2 Geotechnical engineering

Geotechnical engineering-related problems are of the most challenging in the field of civil engineering. It worth noting that wide applications of geotechnical problems in any construction projects have led them to become hot debates for researchers. Application of artificial intelligence, optimization, in particular, found to be significantly efficient for handling this sort of problem. In the following, we provided a review of different applications of metaheuristics to facilitating this sort of problem.

3.2.1 Slope stability analysis

Locating the most critical failure surface in a soil slope has considered an NP-hard type problem. Therefore, it was subject of a large number of studies during the past few decades. Many researchers tried to address this problem by employing optimization algorithms.

Zolfaghari *et al*. (2005) tackled the problem 2D soil slope stability using the GA algorithm. In this study, both homogenous and non-homogeneous soil slopes were examined. Besides, the effect of the presence of a band of weak soil layer was investigated. The results declared that the noncircular slip surface provided more exact solutions. Slip surface developed along the weak soil layer.

Cheng *et al*. (2007) tackled the slope stability problem considering the noncircular slip surface using the PSO algorithm. In this study, the impact of different number of vertical slices on the results were examined using original PSO as well as a modified version of PSO (MPSO). The results revealed the outstanding potential of PSO and MPSO to handle slope stability problem and highlighted shortcoming of classical method in dealing with this problem.

Sun *et al*. (2008) proposed a method based on spline slip surface for soil slopes using GA algorithm. This method was based vertical slice methods where the nodal point at the bottom of each slice were connected by a spline instead of straight line. The efficiency of the developed method was examined via three soil slope samples. It was indicated that considering spline reached the same accuracy as straight line with fewer number of nodal points.

ACO algorithm was proposed to locate the failure surface in soil slopes by Kahatadeniya *et al*. (2009). In this study, the noncircular slip surface was considered in both homogeneous and non-homogeneous soil slopes. Comparison of ACO with some other classical approaches demonstrated its superiority.

Khajehzadeh *et al*. (2010) resolved slope stability problem by paying attention to the failure probability. To that end, a reliability index was defined using the Advanced First-Order Second-Moment (AFOSM) method. Probabilistic point of view confirmed that the most critical slip surface with highest probability of failure may not be equivalent to the failure surface with minimum factor of safety. The obtained results by MPSO found to be better than the original PSO and previously recorded ones.

Khajehzadeh *et al*. (2011b) worked on determination of the most critical slip surface in soil slopes using gravitational search algorithm (GSA). Factor of safety for noncircular slip surface was evaluated using Morgenstern-Price method. The proposed algorithm was examined through some homogeneous and heterogeneous soil slopes in different loading conditions.

Cheng *et al*. (2012) developed a combined optimization algorithm based on PSO and HS (HS/PSO) to handle slope stability problem. Several case studies from homogeneous to non-homogeneous with weak soil layer were handled with this algorithm. The obtained results overcame previously reported solutions.

Kang *et al*. (2013) utilized ABC algorithm for finding the most critical failure surface in soil slopes. Factor of safety was determined using Spencer method and tested through six different soil slope samples. The ABC algorithm performed satisfactorily over all the tackled case studies. Taha *et al*. (2013) developed a hybrid algorithm based on GSA and sequential quadratic programming (SQP) named (GSA-SQP) for slope stability problem. Factor of safety was evaluated using Morgenstern-Price method for three numerical case studies.

Khajehzadeh *et al*. (2014) utilized MPSO to solve slope stability analysis in an effort. They considered the Spencer method and noncircular slip surface to handle several homogenous and non-homogeneous soil slopes. MPSO dealt successfully with slope stability problem in terms of predicting lower factor of safety and less function evaluations.

Hu *et al*. (2015) tried to locate the most critical slip surface using a mutative scale chaos optimization (MSCO). In this study, the authors considered Spencer method with noncircular slip surface. The proposed method was examined through some homogeneous and non-homogeneous soil slopes. Results illustrated that this method found very close factor of safety to the minimum factor of safety in different cases.

Gandomi *et al*. (2015b) considered four swarm intelligence-based techniques (PSO, FA, CS, and levy-Flight krill herd (LKH)) to handle slope stability problem. In that study, the noncircular slip surface with the Morgestern-Price method was considered for analyzing the soil slopes. The obtained results compared to other previously recorded studies and LKH introduced as the best algorithm. Gandomi *et al*. (2015a) highlighted the effect of boundary constraint handling (BCH) method on the performance of algorithms. They investigated this fact by applying two different BCH schemes on CS algorithm and tackled the slope stability problem. The results indicated the importance of BCH methods and cause an increase in the quality of the results found by CS algorithm.

Gandomi *et al*. (2017) employed evolutionary-based techniques (i.e., GA, DE, ES, and BBO) to deal with 2D soil slopes using nonlinear slip surface. Factor of safety in this study was computed using Spencer method. Homogeneous and heterogeneous soil slopes with a band of weak soil layer were examined in this study and BBO found to be the best algorithm. BBO performance was competitive compared with other previously utilized algorithms applied to the same case studies.

Xiao *et al*. (2019) tried to cope with slope stability optimization using enhanced fireworks algorithm (EFWA). The Morgenstern-Price method with a noncircular slip surface was selected for handling this problem. Numerical simulations suggested EFWA as a strongly competitive algorithm in terms of efficiency and accuracy.

Mishra *et al*. (2019) provided a review on the application of swarm intelligence-based algorithms and compared the available works with the antlion optimizer (ALO) algorithm. A nonlinear slip surface with the Spencer method was selected to assess slopes' stabilities.

Mishra *et al*. (2020a) tackled the problem of slope stability using TLBO algorithm. The noncircular failure surface, combined with the Spencer method, was assigned to analyze this problem. Several case studies, including homogeneous and non-homogeneous soil slopes, were explored and results compared to previously accomplished researches. Mishra *et al*. (2020b) inspected the slope stability problem using the multiverse optimization algorithm (MVO). The obtained results indicated that the MVO algorithm is competitive with other available algorithms in other studies.

3.2.2 Concrete cantilever retaining walls

Retaining wall structures are prevalent in most construction projects where stabilizing a trench of unstable soil is a significant concern. Optimum design of retaining walls is of importance because of the massive bulk of material and considerable expenses as a consequence. However, this objective would be challenging because of dealing with a large number of decision variables as well as regulations and limitations to guarantee the serviceability of them. Optimization algorithms found to be efficient for handling this sort of problem. In the following, some efforts in this regard are presented.

Khajehzadeh *et al*. (2011) applied MPSO to the optimization of retaining walls. MPSO proposed to be a modified version of passive congregation PSO (PSOPC). The objective function in this study was defined as the final cost of the structure. A numerical case study was examined using PSO, PSOPC, and MPSO. The impact of retained soil friction angle on the final cost for different height of the wall was studied via sensitivity analysis.

Camp and Akin (2012) addressed the problem of retaining wall optimization using the BB-BC algorithm. They proposed a detailed design procedure based on ACI 318 and using discrete design variables for steel reinforcements. Final cost and weight were considered as the objective functions. The design procedure was validated, and the impact of a base shear key on the final design was studied through two numerical case studies. A sensitivity analysis was conducted to evaluate the role of each effective parameter (surcharge load, backfill slope, and soil friction angle) on the final design.

Khjehzadeh and Eslami (2012) resolved the problem of retaining wall optimization using the same strategy by the GSA algorithm. The design procedure was based on ACI 318 structural limitations, along with several geotechnical matters. The efficiency of the proposed methodology was surveyed through two numerical case studies. GA and PSO benchmarked the performance of GSA in the matter of optimality of solution and convergence rate. Results declared that GSA was more efficient than both GA and PSO.

Gandomi *et al*. (2015c) exploited swarm intelligence-based algorithms (PSO, APSO, FA, and CS) to deal with retaining wall optimization. Two different heights of the wall were designed by those algorithms, and the effect of a base shear was investigated. A sensitivity analysis on the surcharge load, backfill slope, and friction angle of soil was conducted. Low-cost and low-weight were the objective function, and the results proved that CS and PSO performed as the best.

Aydogdu and Akin (2015) used the BBO algorithm to handle minimum CO2 emission and minimum cost design of retaining walls. The design procedure was the basis of ACI 318 limitations and several geotechnical stability requirements. The results of 18 different scenarios based on different objectives and materials were comprehensively discussed.

Temur and Bekdas (2016) utilized three versions of TLBO, including original TLBO, improved TLBO (ITLBO), and modified TLBO (MTLBO) for the optimum cost design of retaining walls based on ACI 318 code. A numerical case study was resolved in this study. As a further study, the tackled example was the subject of sensitivity analysis over the variation of backfill slope, soil friction angle, and surcharge load.

Aydogdu (2017) did a comprehensive study on the optimum design of retaining wall under seismic loading conditions. To this end, a combined algorithm based on BBO and Levy flight (LFBBO) was developed to handle the optimization procedure. The design was conducted for three heights of 5 m, 7.5 m, and 10 m and peak ground acceleration (PGA) varying between 0 and 0.4g. Constraints were defined based on ACI 318 and the American Association of State Highway and Transportation Officials (AASHTOO). The results declared better performance of LFBBO than available results in other studies (HS, FA, AFFA, and BBO). The results highlighted the ineffectuality of seismic hazard analysis with PGA from 0 to 0.2 g while it would be sensible between 0.2 g and 0.4 g.

Gandomi *et al*. (2017a) utilized evolutionary-based algorithms (GA, DE, ES, and BBO) to deal with optimum cost and weight designs of retaining walls. To that end, ACI 318 considerations were incorporated into the design procedure. The settlement of the wall was considered as an additional controlling parameter that was added to the design criteria. A sensitivity analysis on surcharge load, friction angle, backfill slope, modulus elasticity of the soil, and Poison ratio was conducted for a wall with and without a base shear key.

Gandomi *et al*. (2017b) explored the efficiency of interior search algorithm (ISA) in handling the optimum design of retaining walls. In this study, in addition to the finding optimal design values, two objectives were followed: 1- finding the best setting for the only essential parameter of ISA (θ), and 2- finding the best bound constraint handling (BCH) method. To that end, nine combinations of θ values with 12 different BCH schemes were examined.

Gandomi and Kashani (2018a) considered pseudo-static-based design of retaining walls using evolutionary algorithms. DE, ES, and BBO were applied to the design procedure. ACI 318 requirements were incorporated into the design procedure. Two different objectives were defined separately as minimum-cost and minimum-weight. A sensitivity analysis was conducted through nine different combinations of horizontal and vertical seismic coefficients. The results revealed the best performance of BBO in this case.

3.2.3 Foundations

Foundations as an integral part of every structure are significantly vital to guarantee the true functioning and serviceability of the main structure. Depending on the soil type and its bearing capacity, different types of foundations may be considered. Recently, several studies have been devoted to the optimum design of this structural element due to the importance of them. Similar to many other geotechnical structures, foundation problems are challenging and deals with a high level of complexity.

Chan *et al*. (2009) developed a combined, fully stressed design (FSD) approach and GA to handle optimization pile groups. The main objective of this study was the size and topology optimization of pile group foundations. Therefore, the objective function was defined in terms of minimizing material volume as a function of configuration, number, thickness, and cross-sectional dimensions of the piles as design variables.

Leung *et al*. (2013) considered the problem of pile reuse via an optimization approach. This concept was based on adding some new piles to the previously constructed ones and design a new system to endure desired service loads. Therefore, the authors proposed a strategy to find the best configuration of new and old piles for a given objective. A multi-objective approach based upon the ES algorithm (MOES) was supposed to address two objective functions (settlement and material volume) simultaneously. A real-world case study (Bath House project) in central London, UK, was solved in this study where 110 piles targeted to be reused.

Khajehzadeh *et al*. (2011a) applied PSO, PSOPC, and MPSO to the problem of shallow foundation to minimize the final cost value. Several constraints were inserted into the design procedure to provide geotechnical and structural requirements, such as ACI 318 regulations. The effect of bearing factor of safety and settlement as well as soil properties on the final cost was subject to a sensitivity analysis. The results revealed the superiority of MPSO over other algorithms.

Camp and Assadollahi (2013) utilized a hybrid CC-BC algorithm to handle low-cost and low-CO2 emission of a shallow foundation. The design procedure was based upon ACI 318 defined limitations. Design variables were geometry, depth of foundation, and reinforcements. A sensitivity analysis was conducted on the applied load, Poisson ration, elastic modulus of soil, internal friction angle of soil, the factor of safety, allowable settlement, and concrete compressive strength. The trade-off between cost and CO2 emission was explored through multi-objective optimization. The same analysing strategy was utilized by Camp and Assadollahi (2015) to optimize the shallow foundation affected by uniaxial uplift. In this study, MBB-BC took care of minimizing two objectives as cost and CO2 emission, simultaneously.

Gandomi and Kashani (2017) took shallow foundation optimization into account using state-of-art swarm intelligence algorithms (PSO, APSO, FA, LKH, WOA, ALO, GWO, moth-flame optimization algorithm (MFO), and TLBO). In this study, ACI 318 requirements were considered to develop a cost minimization objective function with design variables as geometry, depth, and reinforcement. As a further study, the effect of the column's location at the top of the foundation was explored by defining two additional design variables on one of the case studies. A sensitivity analysis was conducted over depth of foundation, the compressive strength of concrete, the inclination of effective load, soil's friction angel, density, modulus of elasticity, and Poisson ration.

Kashani *et al*. (2019a) did the same study on shallow foundation using evolutionary algorithms including GA, DE, ES, BBO, improved differential evolution algorithm (IDE), weighted differential evolution algorithm (WDE), linear population size reduction success-history-based adaptive differential evolution algorithm (L-SHADE), biogeography-based optimization with covariance matrix-based migration (CMM-BBO).

3.2.4 Miscellaneous geotechnical optimization

In addition to the abovementioned classes of geotechnical engineering problems, there are some other efforts in a wide range of geotechnical engineering subjects. In the following, we presented an overview of the available studies in this regard. Basudhar *et al*. (2008) concentrated on the optimum cost design of reinforced soil retaining wall using sequential unconstrained minimization techniques (SUMT). The design variables in this study were the length of reinforcements and the ultimate long-term strength of reinforcement. Geotextile and geogrid were two available options for this case study. Based on the results, it was mentioned that the optimal cost of the geogrid wall was higher than geotextile because of the modular concrete unit face.

Meier *et al*. (2008) handled the problem of soil and rock inverse parameter identification based on the PSO algorithm. The efficiency of the proposed mechanism was examined by the results of two different laboratory tests and a natural slope. The error between the predicted parameters and observed ones was calculated using the least square error and was treated as the objective function.

Clarke *et al*. (2010) investigated the stability of a sheet pile wall using discontinuity layout optimization (DLO). The analysis was based on numbers of failure mechanisms as wall translation, rigid body rotation, and rigid plastic bending due to developing plastic hinges. The collapse loads obtained in this study compared to the ones resulted from established methods and lower bound finite element method.

Papon *et al*. (2012) utilized single- and multi-objective GA to handle soil parameter identification by an inverse method. GA performance was evaluated by a comparative study with the deterministic simplex method. The objective function for single-objective optimization was inverse parameter identification. For the multi-objective study, this parameter identification was conducted considering two pressuremeter tests. The authors applied the resulted optimized parameters to estimate the response of a spread footing.

Momeni *et al*. (2014) tackled the problem of pile bearing capacity using a hybrid approach. In this problem, a neural network (ANN) was implemented to predict the ultimate bearing capacity of pile given its geometrical properties, pile set, hammer weight, and drop height. GA algorithm was expected to regulate the hyper parameters of ANN in the way to reach its best performance. To this end, a sensitivity analysis over different settings of GA algorithm's parameters as well as ANN's architectures was conducted to catch the best solver. The proposed methodology was applied to a dataset resulted from 50 dynamic load tests on precast concrete piles in Pekanbaru, Indonesia.

Nama *et al*. (2015) tried to use some optimization algorithms (i.e., HS, PSO, and TLBO) to calculate total active earth pressure with and without earthquake loading. A comparison of the obtained results with other common practice approaches confirmed the efficiency of the proposed optimization-based scheme for handling this problem.

Hasanipanah *et al*. (2016) concentrated on the maximum surface settlement sue to tunneling using a hybrid intelligence-based method. To this end a combined PSO algorithm with ANN was proposed to handle the problem using horizontal to vertical stress ratio, cohesion and Young's modulus. The model was developed using 143 datasets obtained from the line No. 2 of Karaj subway, in Iran. The results demonstrated that the horizontal to vertical stress ratio affected the final settlement more than other factors.

Armaghani *et al*. (2017) developed two hybrid approaches based on ICA algorithm combined with ANN (ICA-NN) and PSO algorithm hybridized with ANN (PSO-NN) for predicting penetration rate (PR) of tunnel boring machine performance (TBM) in hard rock. The proposed model dealt with the following effective parameters for predicting PR: uniaxial compressive strength, Brazilian tensile strength, rock quality designation, rock mass rating, weathering zone, and also machine parameters including thrust force and revolution per minute. Two prosed algorithms were fed using a database containing 1286 datasets from the Pahang-Selangor Raw Water Transfer tunnel in Malaysia. Both models were compared based on several measures like coefficient of determination, root mean square error, and variance account for (VAF). The results demonstrated that both hybrid methods performed much better than simple ANN.

Yagiz *et al*. (2018) utilized GA and PSO for predicting rock brittleness based on rock density, uniaxial compressive strength, and Brazilian tensile strength as decision variables. To that end, describing formula was defined as linearly and non-linearly with a set of weighting factors. The objective function was defined in terms of minimizing the error term to find those factors.

Sereshki and Derakhshani (2019) applied some swarm intelligence algorithms (PSO, GWO, and salp swarm algorithm (SSA)) to mechanically stabilized earth with metal strips. The final cost was calculated as a function of a number of strips, width, thickness, length, the horizontal and vertical spacing of steel strips. A retaining structure was designed for a set of soil parameters and four heights of the earth wall. Among the algorithms, PSO performed better for the shorter wall, while GWO was more efficient for taller ones.

Kashani *et al*. (2019b) utilized evolutionary algorithms, including GA, DE, ES, and BBO algorithms for handling MSE walls. In this study, the final cost was evaluated based on the Federal Highway Administration (FHWA) recommendations for both static and pseudo-static loading cases. The design procedure was conducted on several case studies with different heights of walls, backfill slopes, surcharge loads, friction angle of soils, geotextile's strength, earthquake horizontal, and vertical coefficients.

Armaghani *et al*. (2020) proposed a hybrid method based on hybridizing PSO algorithm and ANN to predict the settlement of piles. In this way, a database was extracted from many piles socketed into rock mass from a project in Malaysia named Klang Valley Mass Rapid Transit. A sensitivity analysis on different parameter settings of PSO was conducted to reach its best performance. Moreover, five different hybrid models were generated to obtain the best predictor in this case.

3.3 Other applications

In the following, a review of the application of optimization algorithms to transportation, construction management, and water resource engineering is presented. Lee *et al*. (2005) tried GA to solve adaptive traffic signal control based on real-time traffic conditions. The objective function in this study was defined as minimizing the delay time of vehicles without considering their progressions on all approaches at all intersections in a given time horizon. The results showed that the proposed strategy presented efficient signal control in all the testing scenarios. This problem was reconsidered in another study by Sun and Benekohal (2006) based on a bi-level programming formulation using GA. Incremental logit assignment used to find user optimal flow pattern at the lower level, and cell transmission simulation was in charge of propagating the traffic and collecting real-time traffic information. The results indicated that the system performance improved by 18% as the traffic updating information interval changed from 5 minutes to 1 minute.

Santos *et al*. (2010) studied the capacitated arc routing problem using an improved ACO algorithm. The main concern in this problem is determining the minimum cost for the routes to handle a demand along the edges of a network.

Stevanovic *et al*. (2008) developed a GA-based method combined with a VISSIM microstimulator to optimize traffic control transit priority setting on roads with both private and transit traffic. The mentioned method optimizes all four basic signal timing parameters, including cycle length, green splits, offsets, and phase sequences. Two test cases were surveyed for validation of the proposed methodology: a suburban network of 12 signalized intersections in Park City, UT, and an urban corridor with transit operations in Albany, NY. For the former, GA-based method compared to results of SYNCHRO software and outperform them considerably. In the second case, the proposed method showed improvement in the overall traffic service.

de Souza *et al*. (2010) utilized adapted location based on heuristic (ALBH) for optimization of school bus transportation routes. A real-case study was subjected to be solved in this investigation. The objective of this study was to minimize the total distance traveled by all the vehicles and shrinking the spent time of students inside the vehicles. The primary assumption is that the stop points are mixed, so the student with different schools and degrees may be picked up and dropped by the same route. The solution procedure was based on three main phases: 1- find the better positions of the buses' stops, 2- determine the real distance between all the points, 3- use the proposed optimization-based method to build the routes that give better solutions.

Tan *et al*. (2011) considered the GA algorithm for bus departure scheduling optimization based on satisfying two main objectives as 1- minimizing the number of buses in a day in favor of bus company perspective, 2- minimizing passengers' average waiting time. The proposed methodology was examined for bus scheduling of Zibo city in China.

Mesbah *et al*. (2011) took the optimization of transit priority in the transportation network into account using GA. The main objective was mentioned to optimize the allocated space between private cars and transit modes. The proposed methodology was benchmarked through finding the optimal combination of exclusive lanes for a medium-size example of a network.

Babazedeh *et al*. (2011) applied the PSO algorithm to solve the transportation network design problem. The mentioned problem is a bilevel task that its upper level minimizes the total travel time of the traveler, and the lower level is a traffic assignment model that estimates the traveler flows. The proposed practice was applied to the network of Siouc Falls, and its results compared to previously recorded solutions by ACO and hybridized ACO (HACO). PSO results proved to be better than ACO while they were similar to the ones obtained by HACO but with lower computational efforts.

Shin *et al*. (2011) tackled the problem of temporary hoist planning in high-rise buildings using the GA algorithm. The main objective of this study was to find the optimal hoist plan with minimal time and effort. The proposed methodology was tested by a real experiment and confirmed its efficiency.

Said and El-Rayes (2013) proposed two methods based on GA and approximate dynamic programming (ADP) to handle dynamic site layout planning of a construction project. The objective function was defined as the total site layout cost constituted by travel cost and relocation cost. The mentioned algorithms were examined by two numerical models. ADP outperformed GA in terms of efficiency by finding 6% to 25% lower layout costs.

Cheng and Tran (2014) dealt with the scheduling of the project considering minimization of time and cost using a chaotic initialized multi-objective DE algorithm with adaptive mutation (CAMODE). In this study, the indirect costs of the project considered to be fixed and not related to project activity execution. The total direct cost for a project was calculated as the sum of activities execution costs. A numerical case study was analyzed using the proposed CAMODE, NSGA II, multi-objective DE, and PSO. CAMODE performed better than other algorithms and reflected better diversity characteristics.

Rajguru and Mahatme (2014) provided a review on different applications of optimization algorithms to construction management projects. In this study, the main effort was exploring various factors involved in the final cost of projects through a comprehensive review. In this research, the necessity of developing a systematic approach using optimization algorithms to minimize cost and time of a given project was highlighted.

Yang *et al*. (2016b) tackled flowshop scheduling of multiple production lines for precast production. They used the GA algorithm to search for an optimal schedule. In this study, some deficiencies in the previous studies about the common practice describing models and the applied constraints were addressed through filed observations. The objective function was defined as the average quantity of the types and type changes of precast components in shifts in the production lines.

Vasan *et al*. (2010) applied the DE optimization algorithm to the minimum cost design of water distribution network design. The objective function was defined as evaluating the final cost based on the number of pipes and their lengths and diameters. The design procedure was handled using a combined system based on the DE algorithm with EPANET hydraulic simulation solver. Two real-world case studies were considered: 1- New York water supply system and 2- Hanoi water distribution network.

Ostadrahimi *et al*. (2012) utilized a multi-swarm PSO (MSPSO) combined with HEC-ResPRM simulation model to develop operating rules for a multi-reservoir system. The suggested procedure was assessed for a three-reservoir system in the Columbia River Basin.

Fu *et al*. (2013) proposed a challenge in the optimal design of water distribution systems by handling six objective functions simultaneously. They utilized epsilon NSGA II (ε-NSGA II) to find a trade-off between the following objectives: 1- capital cost, 2- operating cost, 3- hydraulic failure, 4- leakage, 5- water age, and 6- fire-fighting capacity.

Hosseini *et al*. (2016) concentrated on the minimum cost design of the labyrinth spillway. In this study, two combined procedures based on an adaptive neural fuzzy inference system (ANFIS) with DE and with GA algorithm were proposed to handle the design procedure. ANFIS was utilized to predict the discharge coefficient of the labyrinth spillway based on the following factors: 1- the angle between the alignment of the crest and direction of flow, 2- the relative depth of flow over the spillway, and 3- its crest height. Numerical examinations indicated that DE resulted in lower construction costs than GA.

In one of the most recent efforts Kaveh and Eslamlou (2020) explored different applications of metaheuristics to civil engineering problems and covered a wide range of benchmark studies. Rajput and Datta (2020) also provided a comprehensive review on the different applications of optimization algorithms to civil engineering problems.

4. Conclusions

Civil engineering problems deal with a high level of complexity and many variables within their solution space. Hence, in a lot of effort, researchers have tried to facilitate them using state-of-art methodologies. Optimization-based developed solutions have been considered a very efficient approach to handle this line of problems efficiently. Hence, many studies have been devoted to exploring the application of those algorithms to civil engineering problems. Therefore, the large number of available publications in this area calls for some efforts to summarize and classify them and highlight their achievements. In this paper, we aimed to provide a comprehensive review of the application of metaheuristic algorithms to a wide range of civil engineering problems.

Despite a lot of efforts on the application of optimization algorithms to civil engineering problems, there are considerable gaps in different aspects of this field of research. In most of the mentioned problems, the main effort was dealing with only one objective. However, those tackled problems usually deal with more than one conflicting objectives. Therefore, extracting the tradeoff between various objectives and explaining how different factors impact the results would be very important. This sort of information would be helpful for the decision-makers to handle a project more efficiently.

Real-world problems are constraint in general. This fact poses many challenges for optimization algorithms to search the solution space effectively. Thus, a need for developing more robust schemes for handling those constraints is still sensible. Along with that, an essential part of every optimization task is the way a given problem can be defined. A strategy to resolve that can be adopting the problem in a way to satisfy the limitations beforehand and prevent the algorithm from searching infeasible solution space (Gandomi and Deb 2020).

Another major drawback with finding the real applications of optimization to industry is considering a lot of simplifications in defining the problems. Those assumptions may cause going far from the real nature of the problems and not considering the main issues with this problem during the analysis or design procedure. Therefore, it is necessary to minimize simplifying assumptions as much as possible to find more real applications of optimization algorithms. On the other hand, there is no real measure to quantify the performance of algorithms in a way to be able to really assess their efficiency in handling a real-world problem. Therefore, it would be worthwhile to develop a uniform metric for evaluating the potential of each algorithm for handling a problem.

To finish, another potential in this research subject is proposing more practical issues in the civil engineering field. In this way, future researches may benefit from the strong ability of metaheuristics to figure out the issue in real designs. To this end, not to mention developing new problematic problems in different fields of civil engineering, several simplifications for handling a given problem can be eliminated. Therefore, it is worth collecting and develop more benchmark problems in this field. It makes researchers capable of detecting more successful algorithms for handling different problems. Besides, many improvements can be proposed with different strategies to increase the efficiency of those successful algorithms.

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