Population-based Optimization in Structural Engineering: A Review

Ali R. Kashani[1], Charles V. Camp[1], Mehdi Rostamian[1], Koorosh Azizi[1], Amir H. Gandomi[2]

[1]*Department of Civil Engineering, University of Memphis, Memphis, TN 38152, USA*

[2]*Faculty of Engineering & IT, University of Technology Sydney, Ultimo, NSW 2007, Australia*

ABSTRACT

Structural engineering is focused on the safe and efficient design of infrastructure. Projects can range in size and complexity, many requiring massive amounts of materials and expensive construction and operational costs. Therefore, one of the primary objectives for structural engineers is a cost-effective design. Incorporating optimality criteria into the design procedure introduces additional complexities that result in problems that are nonlinear, nonconvex, and have a discontinuous solution space. Population-based optimization algorithms (known as metaheuristics) have been found to be very efficient approaches to these problems. Many researchers have developed and applied state-of-art metaheuristics to automate and optimize the design of real-world civil engineering problems. While there is a large body of published papers in this area, there are few comprehensive reviews that list, summarize, and categorize metaheuristic optimization in structural engineering. This paper provides an extensive survey of a wide range of metaheuristic techniques to structural engineering optimization problems. Also, information is provided on available structural engineering benchmark problems, the formulation of different objective functions, and the handling of various types of constraints. The performance of different optimization techniques is compared for many benchmark problems.

KEYWORD

Engineering optimization; civil engineering; population-based optimization; global optimization; metaheuristic algorithms; structural optimization.

1. INTRODUCTION

Population-based approaches as a subcategory of artificial intelligence (AI)-based methods have proved to be as efficient alternatives to the conventional solvers for highly complex real-world problems. The most significant advantage of these intelligent techniques is that they do not require prior knowledge of the tackled problem. Population-based techniques can be utilized for different tasks, such as prediction and optimization.

The most well-known population-based algorithm for prediction is genetic programming (GP). This algorithm was used in many challenging problems due to its effectiveness. For example Gandomi and Alavai (2012a, 2012b, 2013) utilized a multi-gene GP (MGGP) for material, structural, geotechnical and earthquake engineering problems (Gandomi, Alavi, Gandomi, & Kazemi, 2017; Gandomi, Alavi, Kazemi, & Gandomi, 2014) employed gene expression programming (GEP) to predict shear strength if slender RC beams with and without shear reinforcement, Gandomi et al. (Gandomi, Alavi, & Sahab, 2010) applied linear GP to develop formulation for compressive strength of carbon fiber reinforced plastic (CFRP) confined concrete cylinders, Gandomi, Alavi, & Yun (2011) predicted shear strength of steel fiber-reinforced concrete beams using linear GP, Mousavi, Alavi, Gandomi, Esmaeili, & Gandomi (2010) developed a hybrid approach based on GP and simulated annealing algorithm to predict compressive strength of CFRP-confined concrete cylinders, Gandomi, Mohammadzadeh, Pérez-Ordóñez, & Alavi (2014) utilized a linear GP for predicting shear strength of RC beams without stirrups, Gandomi, Tabatabaei, Moradian, Radfar, & Alavi (2011) introduced a model for predicting the load capacity of castellated steel beams using GEP, Gandomi, Alavi, Kazemi, & Alinia (2009) employed linear GP for behavior assessment of steel semi-rigid joints, Gandomi & Roke (2014) concentrated on the prediction seismic response of braced frames using GP, Gandomi, Roke, & Sett (2013) proposed GP-based model for predicting moment capacity of ferrocement members, and Gandomi, Sajedi, Kiani, & Huang (2016) applied GP to acquire a formulation for concrete creep.

Population-based metaheuristic algorithms perform a meaningful search within the solution space using a set of components that represent potential solutions for the tackled function. These algorithms mimic the intelligence behind natural phenomena to direct the search process. The fundamental assumption in all the metaheuristic techniques is getting close to the optimal solution as much as possible rather than finding the exact final solution. This attitude gives a phenomenal ability to this class of algorithms for handling non-convex, non-smooth, and discontinuous functions. On the contrary, there is no guarantee that the final obtained solution by the algorithm is the best possible choice. This fact has motivated many researchers in recent years to develop new algorithms (Abdel-Basset, Abdel-Fatah, & Sangaiah, 2018; Dokeroglu, Sevinc, Kucukyilmaz, & Cosar, 2019; X.-S. Yang, 2010b; Abualigah et al., 2021; Yang, Chen, Heidari, & Gandomi, 2021) or improve the existing method as much as possible (Gandomi & Deb, 2020; Gandomi & Kashani, 2016, 2018b; Kashani, Chiong, Sandeep, & Gandomi, 2021; Gandomi & Yang, 2012; Gao, Zhang, Sadollah, & Su, 2017; Gupta, Deep, & Mirjalili, 2020; Ngo et al., 2017; Sadollah, Sayyaadi, Yoo, Lee, & Kim, 2018; Tubishat, Idris, Shuib, Abushariah, & Mirjalili, 2020). Metaheuristic techniques can be broadly classified into non-metaphor-based and metaphor-based algorithms, as shown in Figure 1. Metaphor-based algorithms are including bio-inspired (e.g., genetic algorithm (Holland, 1992) and particle swarm optimization (Kennedy & Eberhart, 1995)), art-inspired (e.g., harmony search (Geem, Kim, & Loganathan, 2001) and interior search algorithm (Gandomi, 2014)), science-inspired (e.g., simulated annealing (van Laarhoven & Aarts, 1987) and gravitational search algorithm (Rashedi, Nezamabadi-pour, & Saryazdi, 2009)), social inspired (e.g., teaching-learning-based optimization (Rao, Savsani, & Vakharia, 2011) and school-based optimization (Farshchin, Maniat, Camp, & Pezeshk, 2018)).

Optimization algorithms undertake the engineering problems based on two main standpoints: 1- analysis, 2- design. The main effort in the former is finding the boundary condition where an equilibrium state of a given system is provided. The latter, though, deals with searching for the most optimal configuration of a system that satisfies all the functional requirements. Generally, engineering problems are complicated because of dealing with many design variables and limitations in the form of constraints. On the other hand, due to the stochastic nature of metaheuristics, their performances on different problems are usually variants. Thus, regardless of the problem type, handling them can be considerably challenging for the algorithms. Consequently, the strengths and weaknesses of various algorithms have been reflected in dealing with these challenging problems. Those problems have prone to attract much attention in engineering society and were subject to many sophisticated studies (Bozorg-Haddad, Solgi, & Loáiciga, 2017; Cuevas, Espejo, & Enríquez, 2019; Elshaer & Awad, 2020; Elsheikh & Abd Elaziz, 2019; Ganesan, Vasant, & Elamvazuthi, 2016; Iliopoulou, Kepaptsoglou, & Vlahogianni, 2019; Kumar & Davim, 2019; Pattanaik, Basu, & Dash, 2017; Ramos-Figueroa, Quiroz-Castellanos, Mezura-Montes, & Schütze, 2020; Shaheen, Spea, Farrag, & Abido, 2018; Singh, Tyagi, & Kumar, 2020; G.-G. Wang, Gandomi, Alavi, & Gong, 2019).

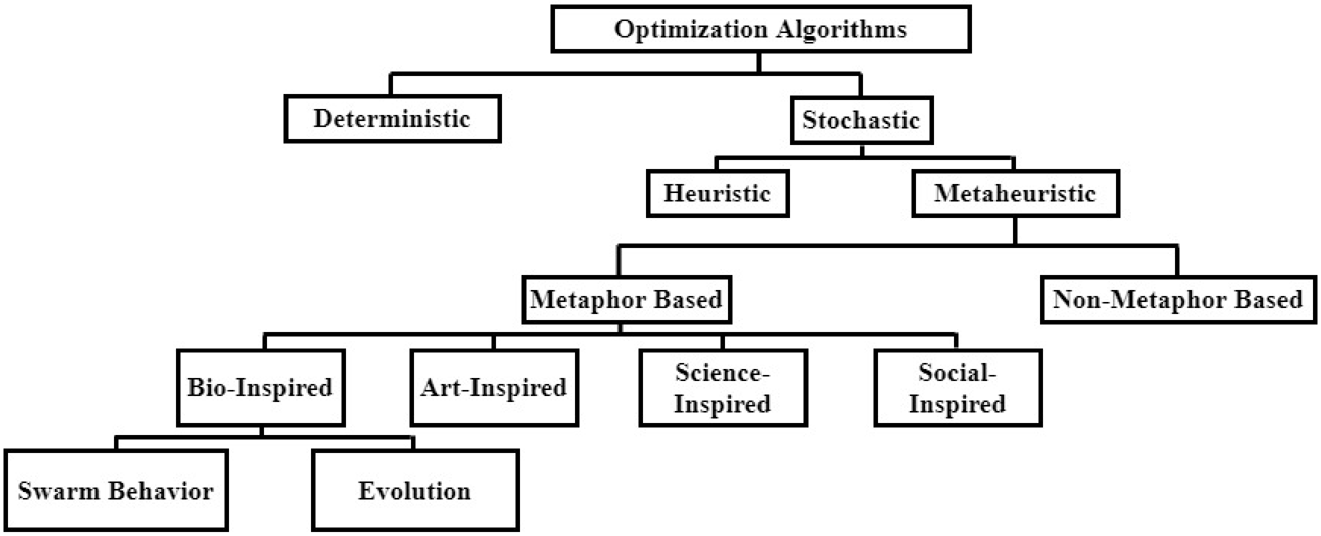

Figure 1. Classification of metaheuristic algorithms.

Civil engineering problems, because of dealing with a large number of decision variables and regulations, are highly complex within their solution space. Optimization algorithms proposed very effective alternatives to this sort of problem, either indirectly or directly. Indirect applications of metaheuristics have been their coupling with some other AI-based techniques such as artificial neural networks (Akhani, Kashani, Mousavi, & Gandomi, 2019; Khari, Armaghani, & Dehghanbanadaki, 2019; Gandomi et al., 2021), genetic programming (Aminian, Javid, Asghari, Gandomi, & Esmaeili, 2011; Gandomi et al., 2008; Gandomi, Alavi, Mohammadzadeh Shadmehri, & Sahab, 2013; Yong et al., 2020), fuzzy logic (Zabihi-Samani & Ghanooni-Bagha, 2019), support vector machine (Hoang & Pham, 2016), random forest (Zhang, Yin, Jin, & Chan, 2020), etc. However, optimization algorithms have been found to be very proficient to directly handle difficult civil engineering problems (Bekdaş, Nigdeli, Kayabekir, & Yang, 2019; Ali Kaveh, 2017; X.-S. Yang, Bekdaş, & Nigdeli, 2016). In this way, the optimal design of a wide range of structures using metaheuristics was modeled mathematically in several efforts (Gandomi, Alavi, & Talatahari, 2013; Gandomi & Yang, 2011; Gandomi, Yang, & Alavi, 2013, 2011; Gandomi, Yang, Talatahari, & Alavi, 2013; Sahab, Toropov, & Gandomi, 2013; Wang, Wang, Xia, & Poh, 2018; Kashani, Akhani, Camp, & Gandomi, 2021). Geotechnical engineering has also been the subject of many investigations (Yang, Gandomi, Talatahari, & Alavi, 2012). For instance, slope stability analysis was examined through different optimization algorithms for many years (Gandomi, Kashani, Mousavi, & Jalalvandi, 2017; Gandomi, Kashani, & Mousavi, 2015; Gandomi, Kashani, Mousavi, & Jalalvandi, 2015; Kashani, Gandomi, & Mousavi, 2016; Sanaeirad & Kashani, 2016); optimum design retaining structures was handled by many researchers to now

(Camp & Akin, 2012; Gandomi, Kashani, & Zeighami, 2017; Gandomi & Kashani, 2018a; Gandomi, Kashani, Roke, & Mousavi, 2015, 2017; Kashani, Saneirad, & Gandomi, 2019; Khajehzadeh & Eslami, 2012; Khajehzadeh, Taha, & Eslami, 2013; Khajehzadeh, Taha, El-Shafie, & Eslami, 2010); shallow foundation optimization was also another important benchmark problem in this field (Assadollahi, 2016, 2017; Assadollahi & Camp, 2014; Camp & Assadollahi, 2013, 2015; Gandomi & Kashani, 2017; Kashani, Gandomi, Camp, & Gandomi, 2019; Khajehzadeh, Taha, El-Shafie, & Eslami, 2011). Many other researchers attempted to explore the efficiency of metaheuristics in handling some other sub-fields of civil engineering such as transportation engineering (Balakrishnan, 2016; Bayram, 2016; Caunhye, Nie, & Pokharel, 2012), water resource management (Jahandideh-Tehrani, Bozorg-Haddad, & Loáiciga, 2020; Oxley & Mays, 2016; Shishegar, Duchesne, & Pelletier, 2018; Moeini, Shojaeizadeh, Geza, 2021), hydraulic engineering (Quaranta & Revelli, 2020; Zhang & Liu, 2018; Azizi, Attari, & Moridi, 2017), and construction management (Eid, Elbeltagi, & El-Adaway, 2018; Sahib & Hussein, 2019; Tavakolan & Nikoukar, 2019; Toğan & Eirgash, 2019).

Recently, an extensive number of metaheuristic algorithms have been developed to address the deficiencies of previously introduced ones as much as possible. Thereupon, numerous investigations have been carried out in which the applications of those algorithms to real-world and benchmark engineering problems are explored. Among all of them, structural engineering related problems have been found to be challenging due to their complex nature. Therefore, they have attracted much attention in engineering optimization research society. However, there is a lack of comparative survey that highlighted the key features of available studies in this area. This research aims to provide a comprehensive review of the different applications of metaheuristics to structural engineering problems. It is worth noting that this review outlined the objective function, applied constraints, design variables, utilized optimization algorithms, and applied modifications just in case. Therefore, the main effort in this review paper can be characterized accordingly: 1- providing a complete list of references on the basis of structural engineering optimization; 2- taking a look at the most updated concerns in structural optimization and their evolution within the time; 3- giving a perspective on the way that new structural problems were defined and addressed using optimization algorithms.

2. SEARCH METHOD PROCEDURE

The searching method of finding the relevant papers for doing the current survey is discussed in detail in this section.

2.1. Search Method

The underlying platform for finding the relevant works of literature was Google Scholar in this study. To do that, we used a software entitled Harzing's Publish or Perish that provides some options for the utilized database to search through. In this review paper, the structural optimization research area was explored based on three main sub-categories: 1- truss structures, 2- frame structures, and 3- miscellaneous. Three keywords were utilized to address these categories for our search within the database as “truss optimization,” “frame optimization,” and “structural optimization.” The output of this software could be saved as a .csv file. The process of searching with those mentioned keywords resulted in a massive number of publications as this software saves every paper recognized with this keyword regardless of its category and field. Therefore, we filtered out all the irrelevant papers to civil engineering. Moreover, we ignored the article published in journals without indexing by Scopus and ISI. Additionally, the published review papers, book chapters, conference papers, and case studies have been excluded during the review.

2.2. Other Reviews

A search through Google Scholar revealed that there are very limited organized review papers in which all aspects of relevant research papers are discussed. Moreover, none of those review papers addressed the structural optimization in specific. Zavala, Nebro, Luna, & Coello Coello (2014) provided a review on the application of multi-objective optimization algorithms to structural optimization. The concepts of multi-objective optimization and Pareto front were explained in this paper. An example of a four-element planar truss considering bi-objective optimization as minimum weight and nodal displacement was examined to clarify multi-objective and Pareto front concepts. Besides, a description of the definitions and classifications of metaheuristics, as well as the issues when solving multi-objective optimization problems, were presented. Along with that, four major attitudes in structural optimization were highlighted as area optimization, size optimization, shape optimization, and topological optimization of cross-sections.

Hajihassani, Jahed Armaghani, & Kalatehjari (2018) explored the application of the PSO algorithm to geotechnical engineering problems. In this review, both direct applications of PSO to geotechnical engineering problems and its application to enhance the performance of other AI-based methods were covered. Before going through the literature review on the geotechnical applications of PSO, different variations of PSO and strong recommendations for parameter settings were discussed. Slope stability analysis, pile and foundation design, rock mechanics, soil mechanics, and tunneling and underground space technology were the main categories of PSO application to geotechnical engineering problems. Furthermore, some geotechnical applications of PSO other than the mentioned major classes were also provided.

Kashani, Chiong, Mirjalili, & Gandomi (2020) provided a comprehensive review and a comparative study on the application of PSO variants to geotechnical engineering problems. In this survey, the fundamental of the PSO algorithm and different tries for modifying and improving its efficiency were argued. In addition, seven main variations of PSO were applied to the benchmark geotechnical optimization problems accordingly: 1- comprehensive learning PSO, 2- heterogeneous comprehensive learning PSO, 3- extraordinary PSO, 4- fractional-order Darwinian PSO, 5- improved random drift PSO, 6- improved PSO based on dynamic parameter setting, 7- autonomous particles groups for PSO. A survey on the available studies on slope stability analysis, retaining wall, reinforced soil, shallow foundation, pile foundations, tunnels, and miscellaneous applications was provided. A comparative study was also conducted on the application of the abovementioned PSO variants to the slope stability, retaining wall, and shallow foundation. Kashani, Gandomi, Camp, Rostamian, & Gandomi (2020) provided a comprehensive review of civil engineering optimization using metaheuristic algorithms in another effort. The general classification of metaheuristic algorithms was expressed in this study. After that, a review was accomplished on many available papers in the field of civil engineering, including structural, geotechnical, transportation, hydraulic and hydrology, and construction management engineering.

3. METAHEURISTIC OPTIMIZATION ALGORITHMS

Metaheuristics, as an integral part of modern optimization, are AI-based techniques proposed by Glover (1986). Despite heuristics, a very important and useful aspect of metaheuristic algorithms is their independence from the characteristics of the tackled problems. Metaheuristics search the solution space stochastically to get close to the optimal solution as much as possible using two main characteristics: 1- exploration, 2- exploitation. In fact, exploration is part of the algorithm that is responsible for global search. This strategy broadens the search area for the algorithm that makes it capable of evading local minima. On this basis, metaheuristics would be applicable to discontinuous and non-differentiable functions easily. On the other hand, exploitation provides a strong local search by shrinking the search space to the area around the most promising up to time region. This phase would be helpful to prevent converging to premature solutions. An appropriate trade-off between those two features—exploration and exploitation—is necessary to reach an efficient performance of the algorithms. Many researchers tried to address this key factor by developing new algorithms mimicking natural phenomena such as sociology, physics, mathematics, art, politics, etc. To now, a wide range of categorizations has been proposed based on their common characteristics. For example, Osman (2003) proposed three clusters for these algorithms as local search, construction-based, and population-based. Gendreau & Potvin (2005) classified metaheuristic techniques into trajectory-based and population-based algorithms. Fister, Yang, Fister, Brest, & Fister (2013) considered two main categories as follows: 1- non-nature inspired, 2- nature-inspired. The following short descriptions are provided for the most well-known metaheuristics.

A genetic algorithm (GA) is the basic evolutionary algorithm modeled the Darwinian theory of natural selection mathematically Holland (1992). The utilized strategy by GA to search the solution space has been a standpoint for developing modern evolutionary-based algorithms. Every potential solution made by design variables is represented by a chromosome of genes. In this way, GA generates a population of chromosomes randomly and adjust those chromosomes' genes through evolutionary operators (i.e., crossover, recombination, mutation, and selection) to improve their fitness. This adjustment would be resulted in producing new generations. This process is repeated until satisfying the termination criteria.

Particle swarm optimization (PSO) is one of the most well-known population-based algorithms that search the solution space by a swarm of particles (Kennedy & Eberhart, 1995). The social behavior of birds flocking for finding foods was the core strategy of the PSO algorithm for finding the optimal solutions. For that reason, every trial solution was equalized as a particle described by two qualities as follows: 1- position, 2- velocity. PSO generates a population of random particles and moves them in the search space using the velocity in every iteration. This velocity term is related to the best-found solution and the best experience of every single particle. By repeating this procedure, more particles would gather around the promising search area to find better solutions. Some other particles, though, will search different sections of solution space to provide exploration.

Geem et al. (2001) developed a harmony search (HS) as a music-inspired algorithm. HS mimics the process of producing aesthetic harmony by the improvisation of musicians through variation. Three major strategies can be employed to achieve this improvisation: 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. HS provides both exploration and exploitation by imitating those three patterns for generating new solutions and solving the tackled problem.

Numerous metaheuristic optimization algorithms have been developed during the past few years. The following list can be made based on the date order to mention some of the well-known algorithms: artificial bee colony (Karaboga, 2010), bees algorithm (Pham et al., 2006), glowworm swarm optimization (Krishnanand & Ghose, 2005); shuffled frog leaping algorithm (Eusuff, Lansey, & Pasha, 2006), cat swarm optimization (Chu, Tsai, & Pan, 2006); imperialistic competitive algorithm (Atashpaz-Gargari & Lucas, 2007), river formation dynamics (Rabanal, Rodríguez, & Rubio, 2009), intelligent water drops algorithm (Hosseini, 2009); gravitational search algorithm (Rashedi et al., 2009), cuckoo search (Yang & Suash Deb, 2009); bat algorithm (Yang, 2010a); spiral optimization (Tamura & Yasuda, 2016); flower pollination algorithm (Yang, 2012), krill herd algorithm (Gandomi & Alavi, 2012c; Kashani, Camp, Tohidi, & Slowik, 2021a; Kashani, Camp, Tohidi, & Slowik, 2021b); cuttlefish optimization algorithm (Eesa, Brifcani, & Orman, 2014), heterogeneous distributed bees algorithm (Tkach, Edan, Jevtic, & Nof, 2013); cooperative group optimization (Xie, Liu, & Wang, 2014), artificial swarm intelligence (Rosenberg, 2016), colliding bodies optimization (Kaveh & Mahdavi, 2014a); the ant lion optimizer (Mirjalili, 2015b), moth-flame optimization algorithm (Mirjalili, 2015a); duelist algorithm (Biyanto et al., 2016), killer whale algorithm(Biyanto et al., 2017m; Kashani, Camp, Armanfar, Slowik, 2020; Kashani, Camp, Armanfar, Slowik, 2021); rain water algorithm (Biyanto et al., 2016), hydrological cycle algorithm (Wedyan, Whalley, & Narayanan, 2017), salp swarm algorithm (Mirjalili et al., 2017); mass and energy balances algorithm (Biyanto et al., 2016); Harris hawks optimization (Heidari et al., 2019), emperor penguins colony (Harifi, Khalilian, Mohammadzadeh, & Ebrahimnejad, 2019); shuffled shepherd optimization algorithm (Kaveh & Zaerreza, 2020), a marine predators algorithm (Faramarzi, Heidarinejad, Mirjalili, & Gandomi, 2020).

4. OVERVIEW ON THE NUMBER OF PUBLICATIONS ON STRUCTURAL ENGINEERING OPTIMIZATION

In the following, we tried to organize available publications on different structural engineering optimization problems. To this end, we used Harzing's Publish or Perish software to do the search within Google Scholar and extract the literature on the targeted field. In the first step, we found a total of 1,961 publications by searching using a keyword as "civil engineering metaheuristic optimization," "structural optimization," and "geotechnical optimization." The software considered all the publications with those keywords. Hence, irrelevant references were filtered by considering only civil-engineering related keywords (i.e., structural, earthquake, geotechnical, transportation, water resource management, hydraulic, and construction management engineering) in their titles. We also excluded dissertations, books, review papers, reliability, and probabilistic optimizations. This strategy resulted in a total of 902 cases from 1997 to 2020, as shown in Figure 2. The observations based on the number of publications in every sub-field is demonstrated in Figure 3. The maximum number of papers in structural and earthquake, geotechnical, transportation, water resource management and hydraulic, and construction management were 77 in 2017, 25 in 2011, 5 in 2016 to 2018, 11 in 2019, and 7 in 2014 and 2019, respectively.

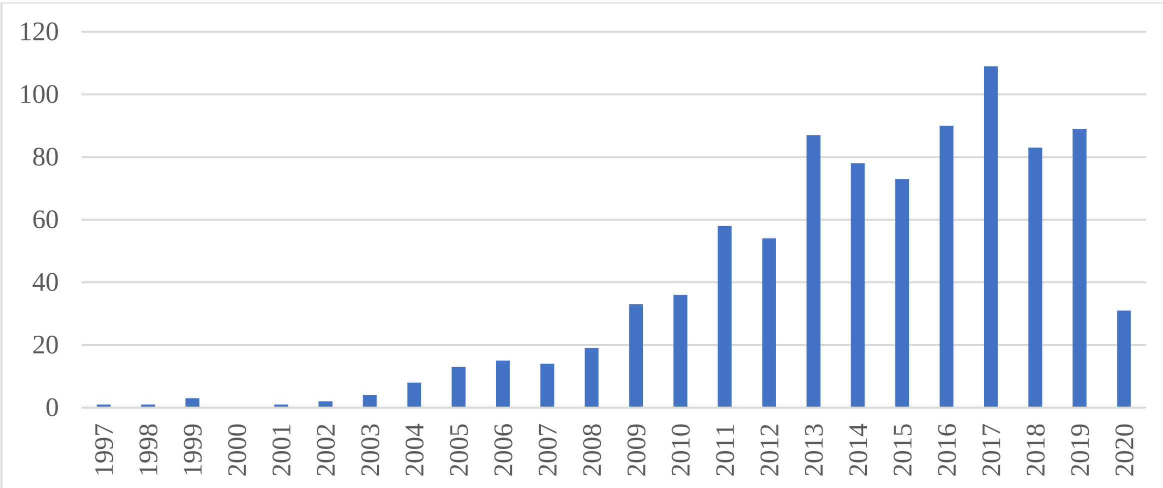

Figure 2. Total number of publications by searching the keywords.

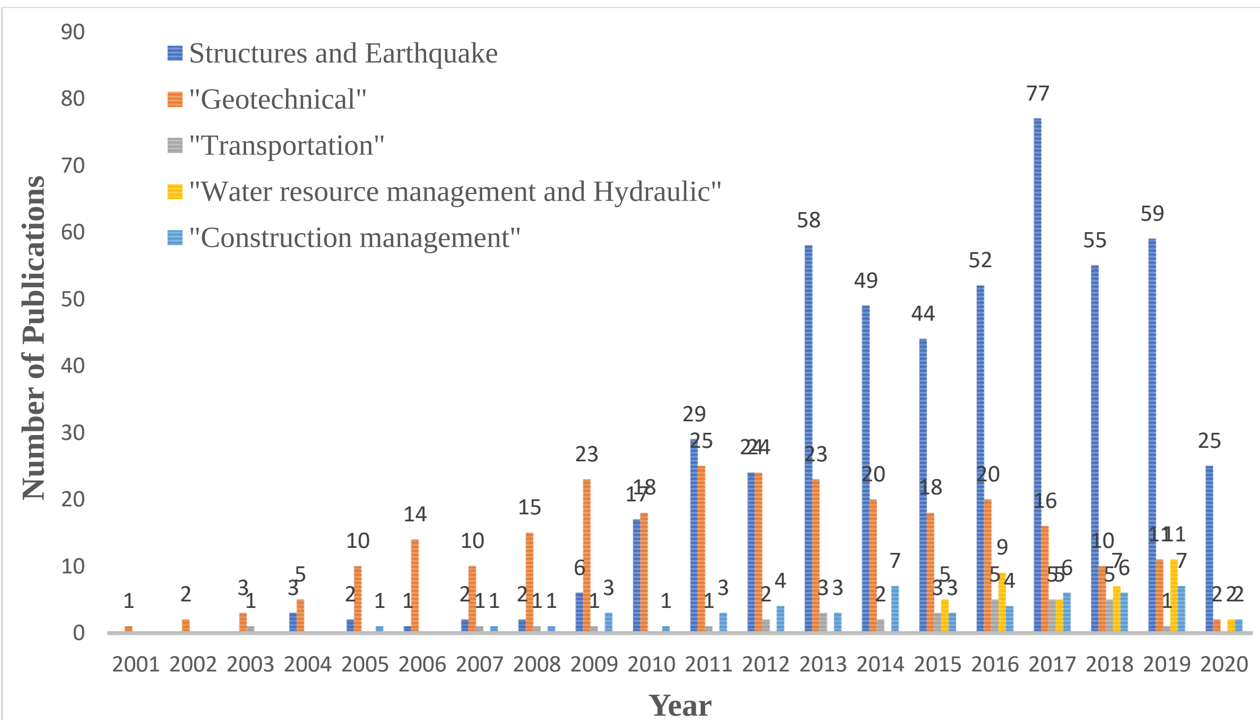

Figure 3. Number of publications in each sub-field by searching the keywords.

The total numbers of publications in each filed were as follows: 507 in structures and earthquake engineering, 273 in geotechnical engineering, 31 in transportation engineering, 39 in water resource management and hydraulic engineering, and 52 in construction management engineering. In order to do the detailed review, we considered only structural engineering optimization papers. In this way, we only considered journals indexed by ISI and Scopus, and we excluded all the conference papers, review papers, books, book chapters, dissertations, technical reports, etc. Therefore, from a total of 507 papers in structural and earthquake engineering, we reviewed 245 papers in three categories as follows: 1- truss optimization, 2- frame optimization, 3- dam optimization, and 4- miscellaneous. Figure 4 depicted the number of publications in each category in different years.

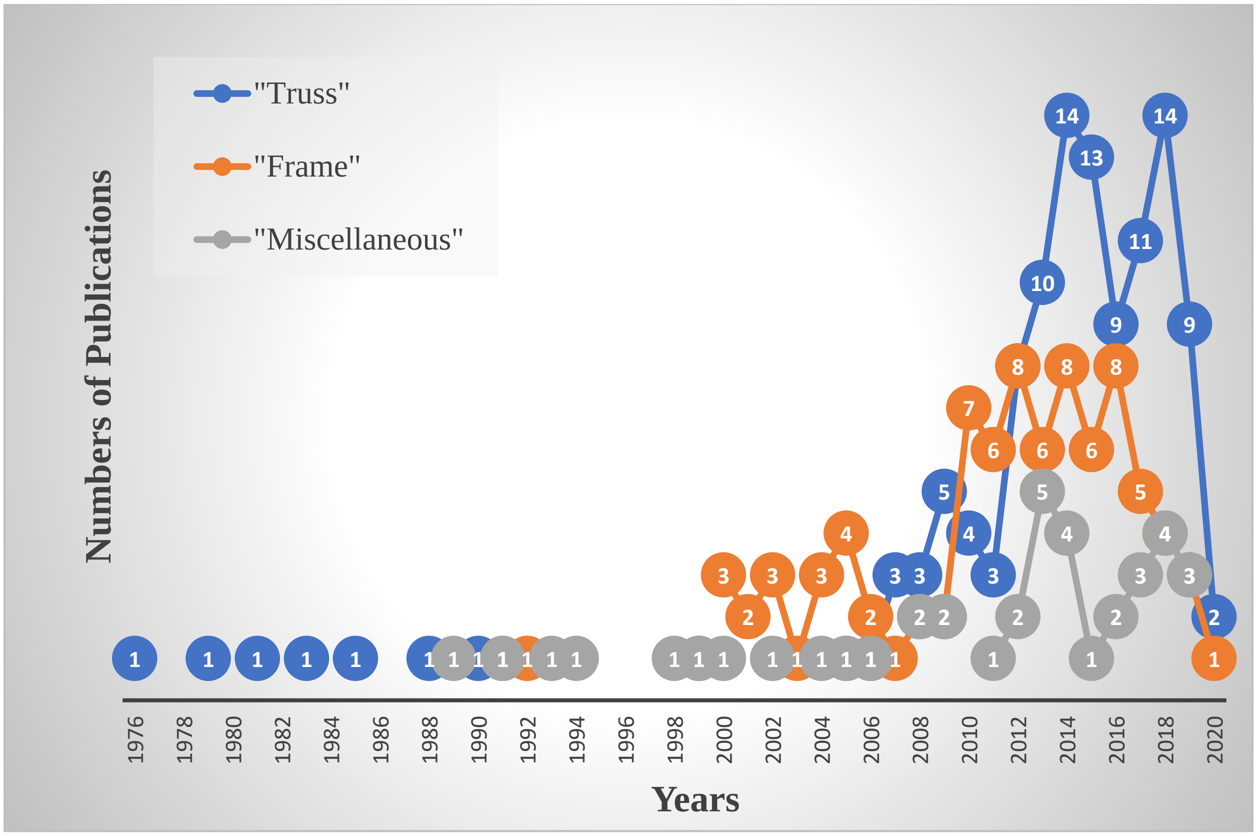

Figure 4. The number of publications in structural optimization using metaheuristics.

From the reviewed publication, we obtained the statistics of publication per journal, and results show the journals of Computer and Structure (35), Structural and Multidisciplinary Optimization (24), and Applied soft computing (22) has published more, among others. Figure 5 provides the data about the most active journals.

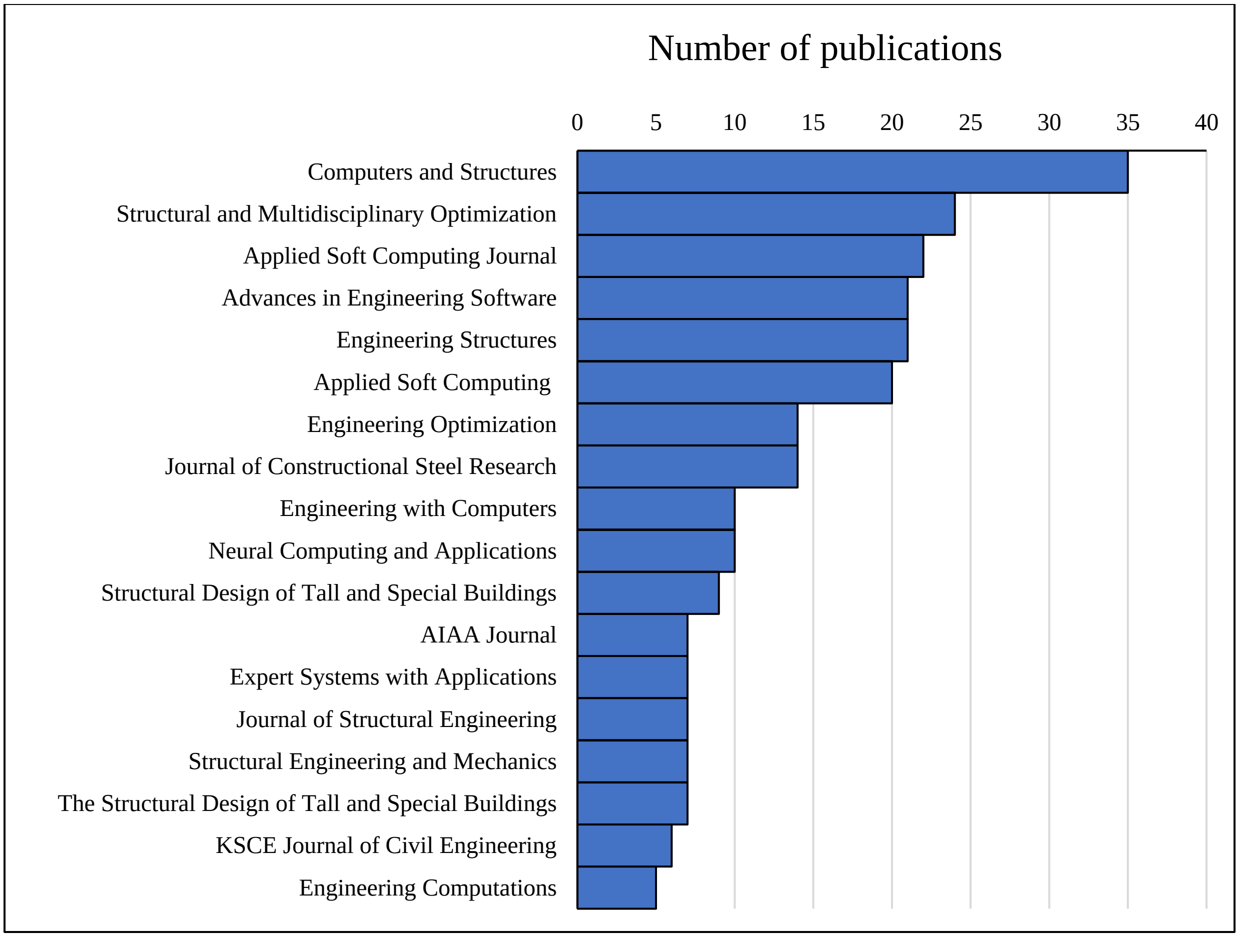

Figure 5. Number of publications per journal

Figure 6 depicts network visualization co-occurrence analysis, and Figure 7 shows the keyword trend in recent years. Each node in the network displays a keyword and the link between the nodes illustrates the co-occurrence of the keywords. From Figure 6, structural optimization, optimization, truss structures, particle swarm optimization, genetic algorithm, frequency constraints, discrete optimization, size optimization, and steel frames among the top useful keywords.

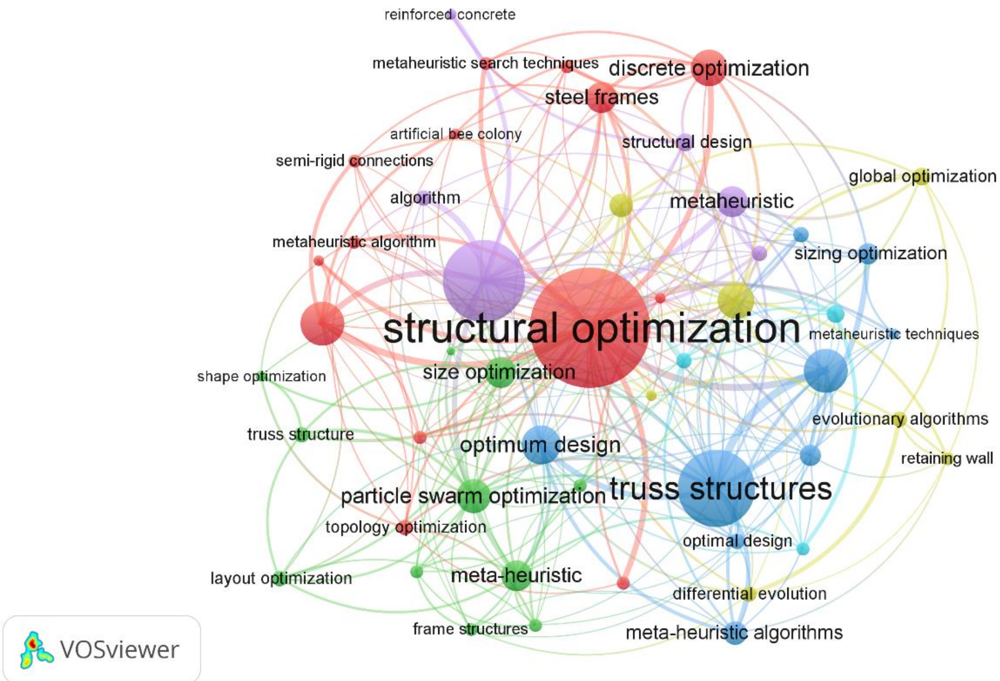

Figure 6. Network visualization

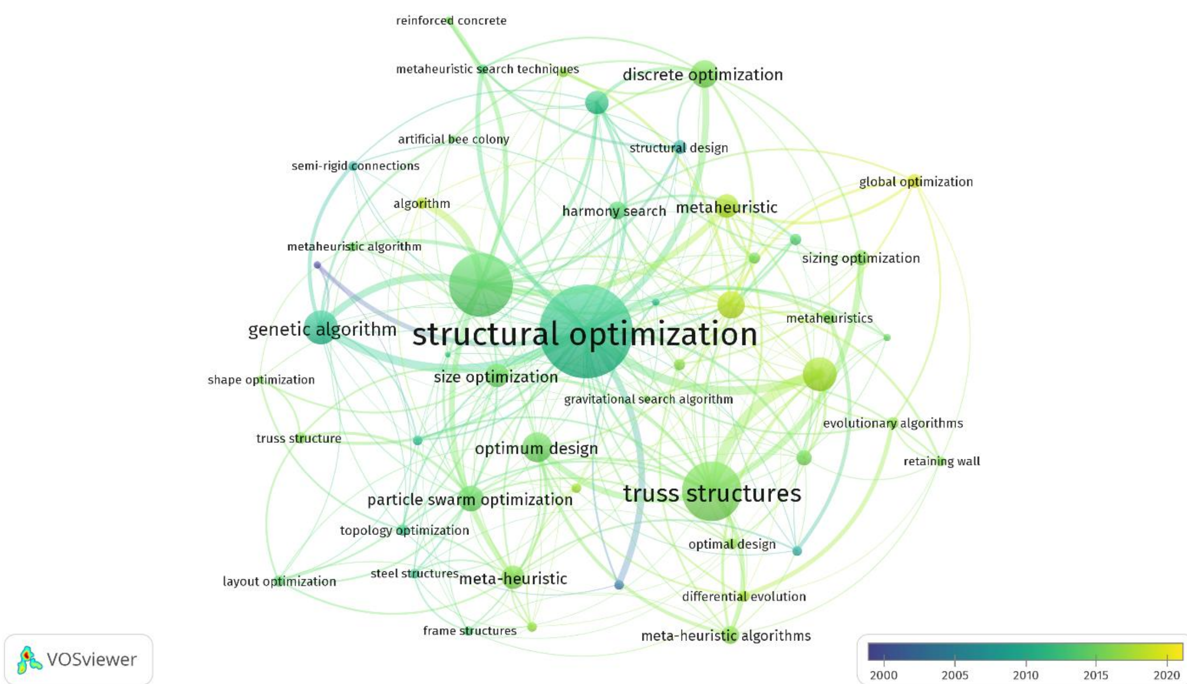

Figure 7. Network visualization trend

Figure 8 shows the networks of total of 610 authors and connections among collaborating researchers. Each node in the network displays an author/ co-author, and the link between the nodes illustrates the co-occurrence of knowledge channels. The networks highlight the scientific communities engaged in research on the entire body of research which was reviewed in the current study.

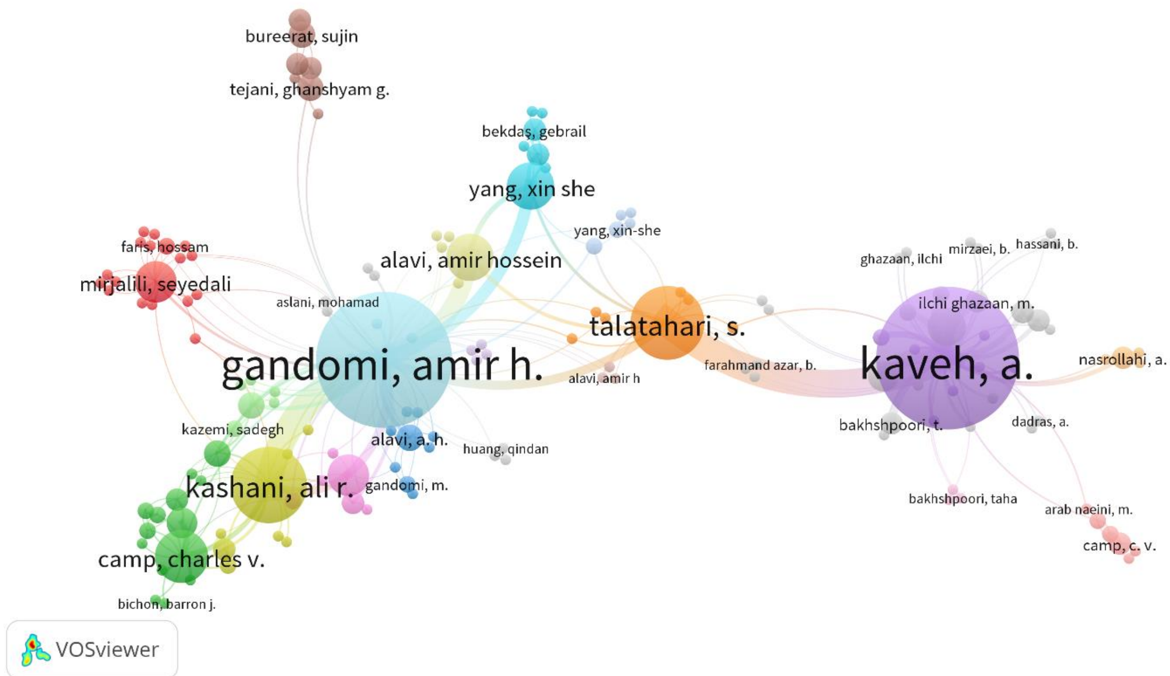

Figure 8. Scientific community (co-author) and collaborations

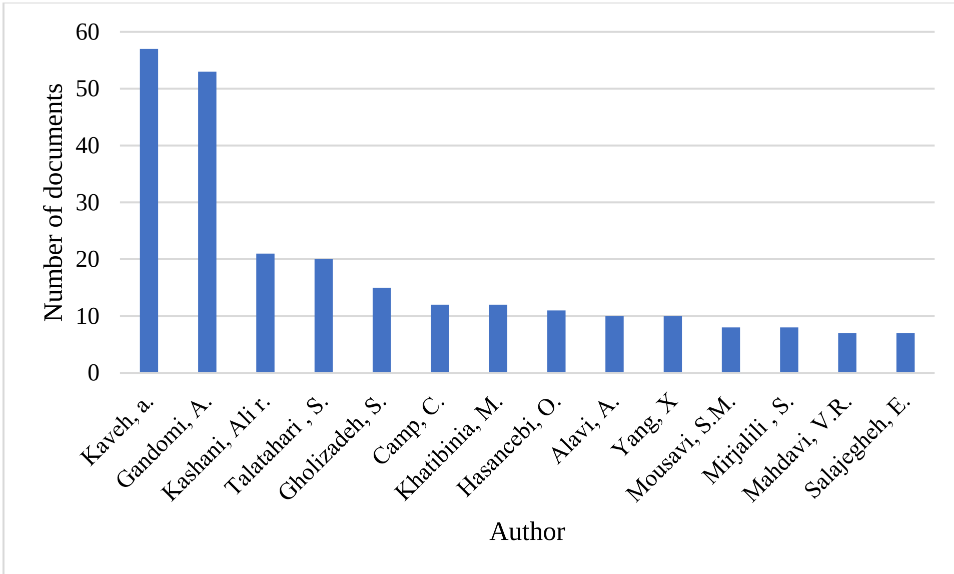

Figure 9. The most active authors in the field

4.1. Truss optimization

In the following review, the detailed explanation is devoted to truss optimization specifically by differentiating between size, shape, and topology for classification. Therefore, we excluded the publications which targeted different engineering problems and solved only one simple truss problem. A general overview of the highlighted key points of the reviewed papers is collected in Table 1. In the following truss optimization related studies are divided into three subcategories based on the tackled objectives: size optimization, size and shape optimization, and size, shape and topology optimization

4.1.1 Size optimization The first paper that considered the optimality of truss structures was published in 1976 (Dobbs & Nelson, 1976). Different criteria and optimization rules were proposed by researchers such as the minimum volume of steel (Khan, Willmert, & Thornton, 1979), minimum mass with constraints on fundamental natural frequency (Bellagamba & Yang, 1981; Grandhi & Venkayya, 1988), nonlinear analysis with constraints on system stability (Khot, 1983), minimum weight with geometric nonlinear behavior (Khot & Kamat, 1985), etc. In 1990, Hajela, 1990 utilized a metaheuristic approach to handle truss structures optimization using GA. In this study, weight minimization was considered as the objective function given nodal displacements constraints. Capriles, Fonseca, Lemonge, & Barbosa (2005) applied five different variations of ant colony optimization (ACO) to the minimum weight design of truss structures. The constraints were stress in each member and displacements in the nodes. Based on the results, the authors proposed a rank-based ant system (AS) as the best algorithm among all the utilized ACO variants. Serra & Venini (2006) studied the application of ACO algorithm to weight minimization of truss structures. The design procedure took strength of elements into account as the constraints. An amplification factor was applied to the compressive elements to model the effect of buckling.

Capriles, Fonseca, Barbosa, & Lemonge (2007) utilized a rank-based ant system (RBAS) for optimum design of truss structures. To this end, discrete design variables were selected for elements' cross-sections. Three different variations of the RBAS algorithm were utilized to solve the tackled problem as follows: 1- RBAS with additive penalty; 2- RBAS with a local update and multiplicative penalization (RBASLU); 3- RBAS with a local update and two-level penalty method (RBASLU,2).

Izui, Nishiwaki, & Yoshimura (2007) tackled the size optimization of truss structures using the PSO algorithm and a combined PSO with sequential linear programming (SLP). The tackled problem was optimized for both single-objective and multi-objective. Three series of case studies were conducted to evaluate the proposed algorithms' performances: 1- weight minimization of truss structures using continuous design variables; 2- weight minimization of truss structures using continuous design variables for the cross-section of elements and discrete design variables for the utilized material; 3- volume and displacement minimization as two conflicting objectives. Gholizadeh, Salajegheh, & Torkzadeh (2007) applied a virtual sub-population (VSP) method (Salajegheh & Gholizadeh, 2005) for weight minimization of truss structures subject to multiple natural frequency constraints. In this study, to reduce the optimization process's computational time, the natural frequencies of structures were evaluated by applying properly trained radial basis function (RBF) and wavelet radial basis function (WRBF) neural networks.

Rahami, Kaveh, & Gholipour, 2008) developed a method based on a combination of energy and force method with GA for truss weight minimization. In this study, the main objective was finding as to the most optimum size, geometry, and topology of the truss structures. In this way, the objective function was defined based on the total weight of the structure, complementary energy, and strain energy.

Hasançebi, Çarbaş, Doğan, Erdal, & Saka (2009) concentrated on the optimum weight design of truss structures using seven optimization algorithms as follows: GA, SA, evolutionary strategy (ES), PSO, TS, ACO, and HS. Steel structure requirements defined by ASD-AISC (Allowable Stress Design Code of American Institute of Steel Institution) were supposed to control the design procedure. ES and SA were found to be more efficient than others, thanks to finding the best solutions in more cases. Kaveh & Talatahari (2009c) developed a hybrid big bang-big crunch (HBB-BC) algorithm to resolve the weight minimization of truss structures. Results from the simulation of several case studies revealed that HBB-BC outperformed the original big bang-big crunch (BB-BC) in finding better solutions. It was indicated that the hybrid algorithms with strong local search ability performed more efficiently than HBB-BC. Kaveh & Talatahari (2009a) developed a hybrid method based on a PSO with the passive congregation (PSOPC), ACO, and HS algorithm called discrete heuristic particle swarm ant colony optimization (DHPSACO) for handling truss optimization problem. Numbers of case studies were selected to evaluate the performance of DHPSACO in comparison with GA, HS, PSO, PSOPC, and HPSO. Results confirmed that DHPSACO resulted in better solutions with less computational time and higher convergence speed.

Rajasekaran & Chitra (2009) utilized the ACO algorithm for the minimum weight design of truss structures under static and earthquake loading. The effect of the essential parameters of ACO on the final results was explored in this investigation. The efficiency of the algorithm is benchmarked through the comparison of the results with the ones resulted from GA with the immune system (GAIS). Kaveh & Talatahari (2009b) developed a hybrid approach based on HS, ACO, and PSOPC algorithms called heuristic particle swarm ant colony optimization (HPSACO) truss optimization. In this algorithm, the PSOPC algorithm did global optimization, and the ACO algorithm provided a local search for updating the position of particles. HS algorithm took care of bound constraint handling, and the fly-back method handled the constraints. Moreover, a termination criterion was proposed based on the amount of variation of the design variables to decrease the number of analyses. A comparison of HPSACO to other PSO-based algorithms showed that the proposed improvements improved the algorithm significantly. The impact of each modification on exploration and exploitation was explored and discussed in that study by detail. Salajegheh, Salajegheh, Seyedpoor, & Khatibinia (2009) solved truss structures' optimization using a particle swam optimization (PSO) algorithm. Design variables were cross-sectional areas of the trusses, and their weights were taken as the objective function. In this study, to reduce the optimization process's computational cost, an Adaptive Neuro-Fuzzy Inference System (ANFIS) was applied instead of performing Finite Element Analysis (FEA) to approximate the nonlinear analysis of the structures. The applied ANFIS model was compared with a Back Propagation Neural Network (BPNN), and results showed that ANFIS produces better performance for structure design values evaluation.

Kaveh & Talatahari (2010) utilized a charged system search (CSS) algorithm for the optimum design of skeletal structures. It was declared that CSS works based on nine rules. Five cases of CSS were proposed to explore the impact of some of those rules on the efficiency of CSS. The authors compared their solutions with numbers of previous efforts such as GA, PSO, HS, BB-BC, HBB-BC, PSOPC, PSACO, HPSACO, and improved ant colony system (IACS). Based on the numerical simulation, it was claimed that CSS was more efficient than the other algorithms. The ability of CSS to find the optimum solution with a smaller number of analyses than other algorithms was mentioned as an advantage of this algorithm. Kaveh & Talatahari (2010b) considered an imperialistic competitive algorithm (ICA) for optimum design of truss structures. The stress in the elements and their slenderness, together with the nodal displacement, governed the search direction. The efficiency of ICA was compared to GA, PSOPC, HPSO, and HPSACO through some case studies. The results confirmed an acceptable performance of ICA in dealing with truss problems. Aragón, Esquivel, & Coello (2010) applied a modified version of a T-cell algorithm for truss optimization problems. In fact, this proposed algorithm was basically an alternative for an artificial immune system (AIS) algorithm adapted to the constrained optimization problems. The results demonstrated that the proposed algorithm handled this problem successfully.

Sonmez (2011b) solved the problem of truss structures' optimization using an artificial bee colony (ABC) algorithm. Discrete design variables were considered in this study to represent the cross-section of structural elements. It was declared based on the numerical simulations that because of a very low difference between the best-found solution and the worst one, ABC was very efficient. Moreover, the execution speed of ABC was mentioned as another advantage of ABC. Sonmez (2011a) incorporated an adaptive penalty function approach to the ABC algorithm (ABC-AP) to handle the weight minimization of truss structures. Numbers of benchmark truss optimization problems were solved using the proposed algorithm and compared to the previously recorded results. It was demonstrated that this algorithm was not the best solver in that comparison, though it dealt with the truss problem successfully.

Sadollah, Bahreininejad, Eskandar, & Hamdi (2012) attempted to solve the weight minimization of truss structures using the mine blast algorithm (MBA). The achieved results compared to several algorithms available in other studies such as steady-state genetic algorithms (SSGA), HS, PSO, PSOPC, HPSO, and DHPSACO. The main advantages of an MBA over other algorithms are mentioned as being efficient in handling large scale problems, fast convergence rate, and low computational cost.

Degertekin (2012) tackled the problem of the optimum size of truss structures using two improved HS called efficient HS (EHS) and self-adaptive HS (SAHS). Two different strategies were proposed for constraint handling. A sensitivity analysis was conducted to monitor the effect of pitch adjusting rate updating and constraint handling strategies. Numerical simulations revealed that both EHS and SAHS were in superiority over the previously utilized algorithms. Besides, they outperformed the conventional HS in all the case studies. Talatahari, Kaveh, & Sheikholeslami (2012) concentrated on the optimum weight design of truss structures using a chaotic ICA algorithm (CICA). The authors proposed four different versions of CICA by using four following chaotic maps for generating random numbers: sinusoidal map, logistic map, zaslavskii map, and tent map. Those modified algorithms compared to the original ICA, orthogonal ICA (OICA), and some previous efforts. The results from two numerical examples approved that the sinusoidal map was more efficient for CICA. Therefore, as a further investigation, two large scale truss structures were analyzed only using this sinusoidal map-based CICA. For those larger structures, CICA performed better than ICA and OICA.

Kaveh & Talatahari (2012a) proposed a hybrid algorithm that combined CSS and PSO algorithms for the optimal design of truss structures. The proposed algorithm was in superiority in comparison with some other previous studies. Kaveh & Zolghadr (2012) tackled the optimum design of truss structures using a combined CSS, BB-BC, and trap recognition capability. The resulting algorithm was an improved CSS with a better exploration. To that end, the authors proposed a method based on recognizing trap conditions through a diversity index and two trap recognition criteria. The resulting BB-BC algorithm pushed the search away from local minima. Comparing the proposed hybrid algorithm with standard CSS and some other algorithms in other studies demonstrated its better performance and more effectiveness.

Gandomi, Talatahari, Yang, & Deb (2013) utilized a cuckoo search (CS) algorithm for the minimum weight design of steel structures. A comparison of the results with previous records demonstrated that CS was more successful than other algorithms for handling tackled case studies. Talatahari, Kheirollahi, Farahmandpour, & Gandomi (2013) proposed a multi-stage PSO (MSPSO) algorithm for the minimum weight design of truss structures. In this MSPSO, two mechanisms were applied to the original PSO: dealing with violated constraints by resetting the velocity term to zero, and handling bound constraints using the content of the global best solution. Talatahari, Gandomi, & Yun (2014) tried FA for the optimum design of tower truss structures. A feasible-based combined with penalty function constraint handling approach was applied to the design procedure.

Degertekin & Hayalioglu (2013) considered teaching-learning-based optimization (TLBO) for the minimum weight design of truss structures. The impact of two parameters settings—the population size (*ps*) and the number of solutions generated in the learning phase (*ndlp*)—were explored through four numerical simulations. The effectiveness of TLBO was proved by comparison with previous efforts in terms of finding more optimum solutions and better convergence capability. It was concluded that increasing ndlp resulted in a decrease in the number of structural analyses. Hasançebi, Teke, & Pekcan (2013) utilized a bat-inspired algorithm (BI) for minimum weight design of truss structures with discrete design variables subject to ASD-AISC's regulations for elemental stress and nodal displacements. Four numerical case studies were analyzed to validate the efficiency of the BI algorithm. Gandomi, Talatahari, Tadbiri, & Alavi (2013) tackled the weight minimization of truss structures using the krill herd (KH) optimization algorithm. The results compared to previously tried algorithms such as GA, SA, PSO, centers and force formulation (CP), augmented Lagrangian methods (AL), and a genetic-Nelder mead simplex algorithm (GNMS) that demonstrated better performance of the KH algorithm.

Kaveh & Khayatazad (2013) applied ray optimization (RO) to size and shape optimization of truss structures. It was mentioned that the RO algorithm performed better than some other standard algorithms such as GA, ACO, PSO, and BB-BC, while it underperformed hybrid approaches like HPSACO.

Lu, Jan, Hung, & Hung (2013) considered weight minimization of truss structures following ASD-AISC rules by enlisting an augmented PSO (AugPSO) based on applying two strategies: 1- boundary-shifting to move the bounds between feasible and infeasible regions, and 2- particle-position-resetting to apply a mutation for increasing diversity. Faramarzi & Afshar (2014) applied a hybridized cellular automata and linear programming (CA-LP) to the minimum weight design of truss structures. A comparison of the obtained results with some other studies proved that CA-LP handled the tackled problem successfully.

Kaveh & Mahdavi (2014c, 2014b) applied colliding bodies optimization (CBO) for optimum design truss structures based on continuous and discrete design variables. The analyses of some numerical examples proved a good performance of CBO in solving truss optimization problems for both continuous and discrete design variables. Kaveh & Zolghadr (2014a) provided a comprehensive comparison between the performance of nine algorithms—PSO, HS, BB-BC, FA, CSS, CS, enhanced RO (ERO), democratic PSO (DPSO), and hybridized PSO and RO algorithm (PSRO)—to handle size and shape optimization of truss structures with natural frequency considerations. The results from the monitoring diversity index proved that DPSO, PSRO, and BB-BC had a good balance between diversification and intensification that ended up to the higher quality of solutions.

Pholdee & Bureerat (2014) conducted a comparative study on the optimum design of truss structures using several metaheuristic algorithms including GA, HS, PSO, stud GA (SGA), differential evolution (DE), ABC, real-code ACO (ACOR), CSS, league championship algorithm (LCA), SA, TLBO, BB-BC, FA, population-based incremental learning (BPBIL), CS, evolution strategy with covariance matrix adaptation (CMAES), continuous population-based incremental learning (CPBIL), continuous scatter search algorithm (CSSA), enhanced continuous tabu search (ETCS), evolution strategies (ES), evolutionary programming (EP), fireworks algorithm (FWA), gravitational search algorithm (GSA), and bat-inspired algorithm (BAT). The constraints were defined based on the natural frequency. Numerical simulations proved that CMAES was the best algorithm due to the lower Wilcoxon rank-sum test as well as finding the lowest mean and standard deviation values in most of the cases. A comparison of the convergence rate showed a better performance of the DE algorithm. Kaveh, Sheikholeslami, Talatahari, & Keshvari-Ilkhichi (2014) enlisted chaotic swarming of particles (CSP) for size optimization of truss structures. CSP utilized chaotic theory in two phases: 1- controlling the parameter values of the particle swarm optimization (CPVPSO), 2- doing a local search (CLSPSO).

Hasançebi & Azad (2014) proposed a refined BB-BC (RBB-BC) algorithm for the design of truss structures based on ASD-AISC. The modified algorithms RBB-BC was capable of finding better solutions than the original BB-BC. Kaveh & Ilchi Ghazaan (2014) applied an enhanced CBO algorithm (ECBO) to the weight minimization of truss structures considering the design criteria defined by ASD-AISC. The original CBO was considered as the benchmark, and the results showed that the proposed modification decreased CBO's sensitivity to the population size. ECBO handled the tackled problem more efficiently than the original CBO. Kazemzadeh Azad & Hasançebi (2014) used a refined self-adaptive step-size (SASS) algorithm called elitist SASS (ESASS) for optimum design of truss structures. To that end, the randomness of the sampling step, an adaptive sampling scheme, and upper bound strategy were incorporated into the ESASS. These modifications were applied in order to increase the convergence accuracy and computational efficiency simultaneously. The results declared that the proposed algorithm satisfied those anticipations successfully.

Khatibinia & Naseralavi (2014) applied an orthogonal multi-gravitational search algorithm (OMGSA) to the optimum shape and size design of truss structures with frequency constraints. In fact, OMSGA is proposed as a combined multi-GSA and orthogonal crossover (OC). Multi-GSA handled sub-population by the main procedure of improved GSA (IGSA). The constraints were handled using the feasibility-based method. Kaveh & Javadi (2014) hybridized HS, RO, and PSO algorithms for optimum size and shape design of truss structures. In the proposed hybrid algorithm (HRPSO), the main optimizer was PSO, while RO and HS handled the global search and local search, respectively. Kazemzadeh Azad, Hasançebi, & Saka (2014) used a guided stochastic search (GSS) technique for discrete optimization of truss structures. Load and Resistance Factor Design-American Institute of Steel Construction (1994) (LRFD-AISC) was considered to control the design criteria. The results indicated the satisfying performance of GSS in comparison to other previous efforts. Camp & Farshchin (2014) concentrated on the optimum weight design of truss structures using a modified TLBO (MTLBO) algorithm. MTLBO worked based on using a fitness-based weighted mean in the teaching phase and a refined student learning system.

Kaveh & Zolghadr (2014b) solved the problem of shape and size optimization of truss structures using a democratic PSO (DPSO). DPSO involved all the valid solutions to update the velocity term and, consequently, the positions of the particles. The proposed algorithm was claimed to be the best solver in handling the tackled problems and compared to other techniques. Oğuzhan Hasançebi & Azad (2015) presented the application of adaptive dimensional search (ADS) for discrete size optimization of truss structures. The ADS algorithm was assessed using two benchmark problems, and the results showed its capability to find a better solution with less computational efforts. Bekdaş, Nigdeli, & Yang (2015) used a flower pollination algorithm (FPA) for the optimum size design of truss structures. An iterative strategy for constraint handling was proposed to incorporate the stress and displacement limitations. The obtained results by FPA were comparative with other previous efforts.

Sadollah, Eskandar, Bahreininejad, & Kim (2015) utilized the water cycle algorithm (WCA), MBA, and improved MBA (IMBA) for discrete optimization of truss structures. The design procedure was governed by ASD-AISC specifications for stress, slenderness, and nodal displacement. Kaveh & Mahdavi (2015b, 2015c) used CBO and a modified version of the CBO algorithm called 2-dimensional CBO (2D-CBO) for the optimal weight of truss structures. Kaveh & Mahdavi (2015a) developed a hybrid approach based on CBO and PSO (CBO-PSO) to handle the same problem. Kaveh & Bakhshpoori (2015) enlisted a procedure called the subspace search mechanism (SSM) to improve the convergence time of the CS algorithm. SSM system tried to divide the search space into a number of sub-spaces by fixing some of the design variables in each subspace. This CS-SSM algorithm was evaluated through several numerical benchmark problems that proved its efficiency to reduce population size and convergence time. However, it was claimed that for complex problems, it might not be accurate enough.

Li & Ma (2015) used a subset simulation optimization algorithm (SSO) for weight minimization of truss structures. The discrete design variables were considered in the simulation procedure using the theory of generating random variables. The effect of five different parameter setting was explored in the simulations. The obtained results by SSO were comparable to other previously utilized approaches. Cheng, Prayogo, Wu, & Lukito (2016) developed a hybrid HS algorithm (HHS) for discrete weight minimization of truss structures. In the HHS algorithm, the randomization function of the original HS was replaced with the global-best PSO search and neighborhood search. A comparative study with other utilized algorithms demonstrated the ability of HHS to find more optimum solutions with a better convergence rate. Bureerat & Pholdee (2016) applied an adaptive DE algorithm (ADEA) to the truss size optimization problem. Different variants of ADEA were formed by changing the functions for adaptation (i.e., linear and exponential) of optimization parameters, and the best combination was introduced. Numbers of constraint handling approaches were also examined during the numerical simulations.

Farshchin, Camp, & Maniat (2016) developed an extension on the TLBO algorithm based on a collaborative optimization strategy called school-based optimization (SBO). In this effort, SBO was selected for optimum size and shape design of truss structures considering the frequency constraints. A sensitivity analysis over the impact of effective parameters on the final results was conducted. Results declared the SBO overcame other techniques in terms of computational robustness and efficiency, especially for more complex cases. Hosseinzadeh, Taghizadieh, & Jalili (2016) utilized a hybrid electromagnetism-like mechanism algorithm and migration strategy (EM–MS) for size and shape optimization of truss structures. EM-MS employed the modified electromagnetism-like mechanism algorithm to provide exploration and the migration strategy for exploitation. It was claimed that the proposed algorithm worked efficiently in terms of convergence speed, stability, and optimality of the solutions.

Kazemzadeh Azad (2017) enlisted six guided optimization algorithms—guided adaptive dimensional search (GADS), guided exponential big bang-big crunch (GEBB), guided modified big bang-big crunch (GMBB), guided adaptive dimensional search-exponential big bang-big crunch (GADS_EBB), guided adaptive dimensional search modified big bang-big crunch (GADS_MBB), and guided adaptive dimensional search-exponential and modified big bang-big crunch (GADS_EBB_MBB)—for minimum weight design of truss structures based on LRFD-AISC requirements. The results compared to the original algorithms (i.e., Adaptive dimensional search algorithm (ADS), exponential BB-BC (EBB), and modified BB-BC (MBB)). Numerical simulations indicated that GADS_EBB was the best algorithm among the other utilized techniques in light of the ease of use, less computational time, and high-quality solutions.

Baghlani, Makiabadi, & Maheri (2017) proposed a constraint handling approach based on mapping the search space to the boundaries of the feasible solution area. The TLBO-MS algorithm was developed by considering this constraint handling scheme and applied to the truss optimization problem. The effectiveness of this method was compared to the penalty function (TLBO-PF) and fly-back (TLBO-FB). Numerical simulations demonstrated that TLBO-MS was better than both TLBO-PF and TLBO-FB. TLBO-MS and TLBO-FB converged to the optimal solutions without constraints violations while TLBO-PF ended up to slightly violated designs.

Kaveh & Ilchi Ghazaan (2017) utilized a vibrating particle system algorithm (VPS) for weight minimization of truss structures based on natural frequency constraints. Jalili, Kashan, & Hosseinzadeh (2017) concentrated on the optimum design of truss structures using the league championship algorithm (LCA). Two different strategies based on the tie concept were proposed to enhance the LCA algorithm (LCA-tie-I and LCA-tie-II). LCA handled the truss problem successfully, and the mentioned modification was found to be effective in enhancing the LCA algorithm.

Krempser, Bernardino, Barbosa, & Lemonge (2017) incorporated local surrogate models into the DE algorithm (SMDE) to solve the truss optimization problem considering both continuous and discrete design variables. The utilized surrogated models were the nearest neighbors' techniques, local linear regression, weighted local linear regression, and RBF Networks. A parameter F was defined to scaler the differences between components of candidate individuals at each surrogate model. Different settings of F values were examined. An adaptive penalty function was considered for combining the constraints into the design procedure. The proposed modifications found to be effective in improving the performance of DE, particularly by using *r*-nearest neighbors using *r*=0.001 and *F*=0.7. Duarte, Lemonge, & da Fonseca (2017) utilized a social spider algorithm (SSA) to weight minimization of truss structures considering stress and displacement limitations. Several case studies were resolved by continuous and discrete design variables.

Pholdee, & Bureerat (2017) tackled Six traditional truss sizing design problems with mass objective function subject to displacement and stress constraints. They considered eighteen self-adaptive meta-heuristics MHs and compared the results in terms of convergence rate and consistency. They found for the problems without buckling constraints, Success-History Based Adaptive Differential Evolution with Linear Population Size Reduction (L-SHADE) and Success-History Based Adaptive Differential Evolution (SHADE) were the top two optimizers. While for buckling constraints problems, LSHADE and L-SHADE with Eigenvector-Based Crossover and Successful-Parent-Selecting were better, respectively.

Kazemzadeh Azad (2018) explored the effect of a modification called seeding the initial population (SIP) with feasible solutions on optimization algorithms' performances. The effect of this enhancement was explored through three optimization algorithms, including ADS, modified BB-BC (MBB-BC), and exponential BB-BC (EBB-BC) for optimum design truss structures. The feeding part was handled based on three different strategies to monitor its effect: 1- no feeding solution, 2- feeding a feasible solution with the largest available cross-sections, and 3- selecting the least violated solution from a pool of randomly generated designs. Moreover, the upper bound strategy (UBS) was applied to the mentioned algorithms to increase their efficiencies. The constraints were defined based on LRFD-AISC regulations. The effect of those modifications was explored and explained based on several numerical simulations. Aslani, Ghasemi, & Gandomi (2018) applied single-solution and population-based mean-variance mapping optimization (MVMO and MVMO-SH) to size minimization of truss structures. The nodal displacement and elemental stress were incorporated into the design procedure as inequality constraints. The adaptive quadratic exterior penalty function method was selected to handle the defined constraints.

Kaveh & Zakian (2018) applied a grey wolf optimizer (GWO) and an improved GWO (IGWO) to the optimal design of truss structures. Beforehand, the impact of the proposed modifications on the GWO algorithm was examined through eighteen mathematical benchmark problems. Results revealed that IGWO outperformed GWO in terms of efficiency, accuracy, stability, and convergence speed. Khatibinia & Yazdani (2018) applied an accelerated multi-gravitational search algorithm (AMGSA) to the optimum size design of truss structures. The AMGSA algorithm was developed based on combining the simplex crossover (SPX) and mutation operator used in breeder GA (BGA) with the GSA algorithm. A sensitivity analysis was conducted over the effect of hyperparameters on the performance of the AMGSA algorithm.

Sonmez (2018) provided a comprehensive comparison between eight metaheuristics in handling truss optimization problem. The effect of the number of iterations in relation to the dimension of problems was compared for the utilized algorithms. The control parameters free algorithms (GWO and JA) and single-parameter algorithm (ABC) performed better than other algorithms. Kaveh, Dadras, & Montazeran (2018) applied a chaotic ECBO (CECBO) algorithm to the optimum design of truss structures. In this CECBO algorithm, some chaotic maps (i.e., Chebyshev, Circle, Gaussian, Liebovitch, Logistic, Piecewise, Singer, Sinus, Sinusoidal, and Tent) were used to control random variables in three ways: 1- changing the probability of colliding bodies, 2- selecting candidate solutions, and 3- regenerating the selected variable by chaos signals.

Cao, Qian, Zhou, & Yang (2018) resolved the truss optimization problem using a subspace HS (SHS) algorithm combined with an improved feasible-base constraint handling approach. A sensitivity analysis over different settings of harmony memory size (HMS) and subspace HMS (SHMS) was conducted. Furthermore, the proposed constraint handling approach was applied to the HS and EHS to provide a more comprehensive comparison. The obtained results compared to the previously recorded results using different optimization algorithms. Gandomi & Goldman (2018) tried the parameter-less population pyramid (P3) for truss optimization with discrete design variables. As P3 is a black-box evolutionary optimization algorithm, the results were compared to some other well-known black-box algorithms, including random restart hill climbing (RRHC), parameter-less hierarchical Bayesian optimization algorithm (PHBOA), DE, and a modified GA. The results were sufficient in terms of convergence speed rather than finding the most optimum solutions.

Baykasoglu & Baykasoglu (2019, 2021) utilized weighted superposition attraction (WSA) for the sizing optimization of truss structures. Jafari, Salajegheh, & Salajegheh (2019) proposed truss optimization using a hybrid approach based on elephant herding optimization (EHO) and cultural algorithm (CA), known as elephant herding optimization cultural (EHOC) algorithm. Degertekin, Lamberti, & Ugur (2019) concentrated on size, shape, and topology optimization of truss structures using an advanced JA algorithm. The proposed algorithm solved this problem using discrete design variables, so it was named after a discrete advanced JA (DAJA) algorithm. A comparison of the results of DAJA with other state-of-art algorithms proved its superiority and promising performance. Jalili & Kashan (2019) tackled the truss optimization problem using optics inspired optimization (OIO). Pouriyanezhad, Rahami, & Mirhosseini (2020) explored the truss optimization problem using the eigenvectors of the covariance matrix (ECM) inspired by the covariance matrix adaptation evolution strategy (CMA-ES). In this algorithm, a dynamic penalty function was considered to incorporate the constraints into the design procedure. ECM was compared to some other algorithms (i.e., whale optimization algorithm (WOA), GSA, GWO, and PSO) in terms of final solutions optimality, stability, and convergence rate.

4.1.2. Shape optimization

Shape optimization of truss structures minimizes the weight by changing the elements' sizes and nodal positions given a fixed number of elements and topology. Kaveh & Shahrouzi (2007) developed a hybrid algorithm based on ant strategy and a GA for size and layout optimization of truss structures. This hybrid approach aimed to adjust the GA population size in every single run to enhance its performance. Population tuning in this algorithm was handled using the indirect data share strategy of AS. The final objective function in this study was the total weight of structure given elemental stress and nodal displacement limitations. The results revealed that the population size increase was stopped after finding the global optimum solution. Moreover, using the proposed strategy resulted in less computation effort and better convergence rate to global optimum Another advantage of this hybrid method was mentioned as finding the global optimum solution in a single run. It was shown that the population size was related to the convexity of the problem on the one hand and other GA parameters, on the other hand. Therefore, this hybrid approach was helpful in eliminating the parameter setting step for GA.

Kaveh & Talatahari (2011) developed an improved CCS algorithm using the concept of fields of forces (FOF). This algorithm was applied to the problem of shape and size optimization of truss structures. The original CSS algorithm was considered as a benchmark to evaluate the performance of the proposed algorithm. This enhanced algorithm proved to be efficient in handling the selected problems. Miguel & Miguel (2012) tackled truss size and shape optimization problems considering natural frequency constraints. HS and firefly algorithm (FA) automated the design procedure. A series of 2D and 3D truss structures were subjected to evaluate the effectiveness of the proposed algorithms compared with some earlier efforts. Although the elapsed time for the HS algorithm to converge the optimal solution was less than FA, in all the cases, FA ended up with better solutions.

Gholizadeh (2013) developed two combined approaches based on cellular automata (CA) and PSO for shape optimization of truss structures. The proposed hybrid approaches were a novel CA-based PSO scheme called CPSO and a sequential cellular PSO called SCPSO algorithm. Moreover, a cellular PSO (CPSO) was considered for simulations. The sensitivity of the essential parameters of this algorithm was examined through four case studies, and the best combination was proposed. Gholizadeh & Barzegar (2013) tackled shape and size optimization of truss structures based on frequency constraints using an enhanced HS (EHS) and sequential EHS (SHS) algorithms. A sensitivity analysis was performed on the different essential parameter settings of the algorithm. The numerical simulation results declared that EHS performed better than simple HS, and SHS was better than both HS and EHS. Shojaee, Arjomand, & Khatibinia (2013) applied a combination of improved discrete particle swarm optimization (IDPSO) and method of moving asymptotes (MMA) for size and layout optimization of the truss structures. The results showed that the hybrid of IDPSO and MMA could accelerate the convergence rate and reach the optimum design quickly.

Dede & Ayyaz (2015) applied the TLBO algorithm for size and shape optimization of truss structures. The investigators of this study confirmed the ability of TLBO to handle the tackled problem effectively based on providing a comparative study with other algorithms. Kaveh & Ilchi Ghazaan (2015) applied two combined algorithms to an optimum size and shape design of truss structures considering frequency constraints as 1- hybrid PSO and aging leader and challengers (ALC-PSO), and 2- harmony search-based ALC-PSO (HALC-PSO). Kaveh, Mirzaei, & Jafarvand (2015) tackled truss structure optimization using an improved magnetic charged system (IMCSS) that hybridized an improved HS (HIS) and the magnetic charged system (MCSS). Ho-Huu, Nguyen-Thoi, Nguyen-Thoi, & Le-Anh (2015) applied an improved constrained DE (D-ICDE) for size and shape optimization of truss structures. Based on the results, D-ICDE handled the truss optimization problem effectively in terms of finding a more optimum solution with less computational effort.

Pham (2016) applied an enhanced DE (ANDE) to the truss optimization problem. Basically, ANDE considered three major modifications as 1- using P-best strategy to balance global and local search, 2- applying directional mutation rule to improve the solution, and 3- using the nearest neighbor comparison method to ignore unpromising solutions beforehand. P-best strategy randomly selects an individual from the top P solutions for mutation. Success-History based Adaptive Differential Evolution (SHADE) with Linear decrease in population size (L-SHADE) was also utilized for handling the optimization procedure. ANDE evaluation through numerical simulations proved that it was comparable to other sophisticated algorithms. Different settings for *P*-value were assessed in the numerical simulations. The results from simulations confirmed the satisfying performance of ANDE. Farshchin, Camp, & Maniat (2016) attempted to solve truss size and shape optimization using a multi-class TLBO algorithm (MC-TLBO). MC-TLBO worked based on two phases, including 1- search the solution space through parallel classes, and 2- the best solutions in the first phase were selected to initialize the population for a modified TLBO. The effect of the different number of classes was explored in the numerical simulations.

Ho-Huu, Vo-Duy, Luu-Van, Le-Anh, & Nguyen-Thoi (2016) investigated the capability of an improved DE algorithm based on adaptive mutation (IDE) in handling truss structure optimization. The design procedure was planned based on weight and layout optimization given to natural frequency requirements. The improvements applied to IDE was imposing a new selection strategy to mutation operator. The performance of IDE was assessed through a comparison with DE and some other utilized techniques for handling numerical simulations. Moreover, two other variations of DE called the elitist selection technique (eDE), and the DE with the proposed adaptive mutation strategy (aDE) were applied to one of the tackled problems to see the effect of applied modifications. The proposed IDE algorithm was able to find solutions similar to or better than DE with less computational efforts.

Kaveh & Zolghadr (2017) applied the cyclical parthenogenesis algorithm (CPA) to the layout optimization of truss structures based on dynamic considerations. A comprehensive study was conducted against different combinations of essential parameters of this algorithm. A comparison of the obtained results with some other algorithms confirmed that CPA handled the tackled problem satisfactorily. Cao, Qian, Chen, & Zhu (2017) took an enhanced PSO (EPSO) for optimum size and layout design of truss structures. The applied modification to the PSO algorithm was using a particle categorization strategy for the sake of decreasing the number of analyses and increasing computational efficiency. In this study, a parameter, R, was defined to count the number of trials that need to be checked for constraint violations. The results from numerical analyses were discussed based on statistical approaches, R, convergence rate, and computational time. The effect of hyperparameters was examined through the simulations. EPSO was found to be more efficient than PSO in terms of computational effort without affecting constraint violations. Kanarachos, Griffin, & Fitzpatrick (2017) optimized the size and layout of truss structures using a contrast-based fruit fly optimization algorithm (c-mFOA).

Kazemzadeh Azad, Bybordiani, Azad, & Jawad (2018) employed the BB-BC algorithm for size and layout optimization of truss structures given different dynamic excitations. To that end, LRFD-AISC considerations with discrete design variables were the basis of the design procedure. Periodic loadings with different periods as well as the finite rise time of non-periodic step force. Jalili & Hosseinzadeh (2018) developed a hybrid optimization algorithm based on DE and biogeography-based optimization (BBO) algorithms (BBO-DE) for truss structure optimization. In this algorithm, DE took care of a mutation mechanism to provide exploration. Moreover, a modified migration operator was applied to strengthen the local searchability. The performance of the BBO-DE algorithm was examined through several case studies and compared to the previously utilized algorithms as well as the original BBO and DE algorithms. Ho-Huu, Nguyen-Thoi, Truong-Khac, Le-Anh, & Vo-Duy (2018) developed an improved DE based on roulette wheel selection (ReDE) to deal with size and shape optimization of truss structures with frequency constraints. Two modifications were applied to ReDE as follows: 1- using roulette wheel selection for the mutation phase, and 2- using an elitist selection technique to improve the convergence speed. Lieu, Do, & Lee (2018) applied a combined algorithm based on FA and DE called novel adaptive hybrid evolutionary firefly algorithm (AHEFA) to truss optimization problems. An adaptive mutation operator is utilized according to the difference between the best-found solution and the whole population at the previous generation. The proposed AHEFA improved considerably in terms of convergence speed compared to DE and FA. Carvalho, Lemonge, Carvalho, Hallak, & Bernardino (2018) studied the effectiveness of craziness-based PSO (CRPSO) with an adaptive penalty method. Natural frequency constraints, as well as cardinal constraints for automatic member grouping, were considered in the design procedure.

Tejani, Kumar, & Gandomi (2019) utilized a multi-objective HTS algorithm (MOHTS) for weight minimization and nodal displacement maximization for truss structures, simultaneously. The results compared to some other methods like MOAS, MOACS, and MOSOS. Millan-Paramo & Filho (2019) tried to enhance the modified SA (MSAA) algorithm by combining it with the WWO algorithm. Kaveh & Mahjoubi (2019) applied a hypotrochoid spiral optimization approach (HSPO) for size and layout optimization of truss structures. The obtained results were compared to the original method spiral optimization algorithm (HSPO) to observe the effect of those modifications. Le, Bui, Ngo, Nguyen, & Nguyen-Xuan (2019) hybridized the electromagnetism-like mechanism (EM) and FA to introduce the EFA method for optimum design of truss structures. The feasible-based approach was utilized for incorporating the constraints that resulted from stress, buckling, and displacement. Liu, Zhu, Chen, & Cao (2020) combined an adaptive vision search strategy with a fruit fly optimization algorithm (FOA). The optimization procedure was based on weight and layout optimization considering natural frequency constraints. In order to apply constraints, an improved, feasible-based constraint handling approach was considered in this study. The obtained results compared with previous efforts on similar case studies.

4.1.3. Topology optimization

The final strategy in optimal design of truss structures is deciding about the presence of elements in addition to the nodal position and elements' sizes. Luh & Lin (2008) utilized an ant algorithm to handle optimum size, shape, and topology of truss structures. The proposed ant algorithm was based on a two-stage strategy combining AS and API (after "apicalis" in Pachycondyla apicalis) algorithms. In this way, AS took care of fining optimal topology while the API search for optimum size and shape. The optimization procedure proposed to be weight minimization given providing the following criteria: 1- user satisfaction, 2- kinematic stability, 3- elemental stress capacity, 4- nodal displacement.

Kaveh & Zolghadr (2013) used the CSS algorithm for topology optimization of truss structures based on static and dynamic constraints. A comparison of the results obtained by CSS with PSO and previous efforts proved the better performance of CSS for handling the tackled problems. Miguel, Lopez, & Miguel (2013) explored the application of the firefly algorithm (FA) for size, shape, and topology of truss structures. Two phases were considered for the simulations as: with and without slenderness related constraints. Discrete design variables were considered for cross-section areas, while the nodal positions were defined by continuous variables. Gonçalves, Lopez, & Miguel (2015) used the search group (SG) algorithm for discrete size, shape, and topology optimization of truss structures.

Savsani, Tejani, & Patel (2016) studied the topology optimization of truss structures using a modified subpopulation TLBO (MS-TLBO). In this study, both static and dynamic constraints were considered during the design procedure—the presented modifications were found to be effective in enhancing the performance of the TLBO algorithm. Mortazavi & Toğan (2016) proposed an integrated PSO (iPSO) for optimum size, shape, and topology design of truss structures. iPSO incorporated weighted particle definition and improved fly-back constraint handling scheme into the PSO algorithm.

Savsani, Tejani, Patel, & Savsani (2017) explored the effect of using random mutation on the performance of four metaheuristic algorithms (i.e., heat transfer search (HTS), water wave optimization (WWO), passing vehicle search (PVS), and TLBO) in truss topology optimization. These modified algorithms—MHTS, MWWO, MPVS, and MTLBO—were evaluated through several benchmark problems, and MPVS was found to be the best algorithm among all the techniques.

Tejani, Savsani, Bureerat, & Patel (2018) applied some modifications to the symbiotic organisms' search (SOS) algorithm for the sake of increasing its efficiency in handling optimization of truss structures. To that end, an adaptive mutation was incorporated into this modified SOS (MSOS) algorithm. Degertekin, Lamberti, & Ugur (2018) applied the Jaya algorithm (JA) for size, shape, and topology optimization of truss structures. JA was applied to several benchmark problems and compared to a wide range of state-of-art algorithms. The statistical analysis of the results showed its efficiency in handling the tackled problems.

Table 1. Review of the application of metaheuristic algorithms to truss structures.

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Design Criteria
Hajela (1990)	1990	GA	-	Weight minimization	- Nodal displacements
Capriles, Lemonge, & Barbosa (2005)	2005	ACO variants: Ant System, Ant Colony System, Max-Min Ant System, Rank Based Ant System, and Best-Worst Ant System	GA with adaptive penalty technique	Weight minimization	- Elemental stresses - Nodal displacements
Serra &Venini (2006)	2006	ACO	-	Weight minimization	- Elemental stresses - Elemental buckling
Capriles, Fonseca, Barbosa, & Lemonge (2007)	2007	RBAS, RBASLU, RBASLU,2	APM and SSGA	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacements
Kaveh & Shahrouzi (2007)	2007	Hybrid ant system and GA	GA	Size and shape optimization	- Elemental stresses - Nodal displacements
Izui, Nishiwaki, & Yoshimura (2007)	2007	PSO, hybrid PSO and SLP	-	1- single objective: weight minimization 2- multi-objective: volume and nodal displacement minimization	- Elemental stresses - Nodal displacements
Gholizadeh, Salajegheh, & Torkzadeh (2007)	2007	VSP	-	Weight minimization	- multiple natural frequency constraint
Luh & Lin (2008)	2008	Combined AS and API	-	Size, shape and topology optimization	- Acceptability to the user - Elemental stress - Nodal displacement - Kinematical stability

Table 1. Review of the application of metaheuristic algorithms to truss structures.

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Design Criteria
Rahami, Kaveh, Gholipour, & Sizing (2008)	2008	GA	GA variants	Weight minimization based on combined energy and force method	- Elemental stresses - Elemental buckling - Nodal displacement
Hasançebi, Çarbaş, Doğan, Erdal, & Saka (2009)	2009	GA, SA, ES, PSO, TS, ACO, and HS	-	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Kaveh & Talatahari (2009)	2009	HBB-BC	GA, PSO, ACO, and HS	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Kaveh & Talatahari (2009)	2009	DHPSACO	GA, HS, PSO, PSOPC, and HPSO	Weight minimization	- Elemental stresses - Nodal displacement
Rajasekaran & Chitra (2009)	2009	ACO	GAIS	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Salajegheh, Salajegheh, Seyedpoor, & Khatibinia (2009)	2009	PSO, ANFIS	-	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacements
Kaveh & Talatahari (2009)	2009	HPSACO	HS, PSO, PSOPC, HPSO, and PSACO	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Kaveh & Talatahari (2010)	2010	CSS	GA, PSO, HS, BB-BC, HBB-BC, PSOPC, PSACO, HPSACO, and IACS	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement

Table 1. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Design Criteria
Kaveh & Talatahari (2010)	2010	ICA	HBB-BC, PSOPC, PSACO, HPSACO, and CSS	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Aragón, Esquivel, & Coello (2010)	2010	T-Cell	-	Weight minimization	- Elemental stresses - Nodal displacement
Sonmez (2011)	2011	ABC	GA, SA, ACO, and HPSO	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Kaveh & Talatahari (2011)	2011	FOF-based CSS	GA, PSO, HS, PSACO, HPSACO, HBB-BC, and CSS	Size and shape optimization	- Elemental stresses - Elemental buckling - Nodal displacement
Sonmez (2011)	2011	ABC-AP	HS, PSO, SA, and HPSO	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Miguel & Miguel (2012)	2012	HS and FA	GA and PSO	Size and shape optimization	- Natural frequency
Sadollah, Bahreininejad, Eskandar, & Hamdi (2012)	2012	MBA	SSGA, HS, PSO, PSOPC, HPSO, and DHPSACO	Weight minimization	- Elemental stresses - Nodal displacement
Degertekin (2012)	2012	SAHS and EHS	HS, PSO, HPSO, BB-BC, HBB-BC, HPSACO, and CMLPSA	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Talatahari, Kaveh, & Sheikholeslami (2012)	2012	ICA, OICA, and CICA	GA, SA, HS, PSACO, HPSACO, and HBB-BC	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement

Table 1. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Design Criteria
Kaveh & Talatahari (2012)	2012	PSO-CSS	GA, PSO, BB-BC, HBB-BC, and CSS	Weight minimization	- Elemental stresses - Nodal displacement
Kaveh & Zolghadr (2012)	2012	Hybrid CSS-BBBC with trap recognition capability	GA, PSO, and CSS	Weight minimization	- Natural frequency
Kaveh & Zolghadr (2012)	2012	CSS	PSO	Weight and Topology optimization	- Elemental stress - Elemental buckling - Nodal displacement - Natural frequency
Gandomi, Talatahari, Yang, & Deb (2012)	2012	CS	GA, PSO, SA, ABC, ES, BB-BC, PSACO, and HPSACO	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Talatahari, Kheirollahi, Farah-mandpour, & Gandomi (2012)	2012	MSPSO	GA, HS, ACO, PSO, HPSO, CSS, and HBB-BC	Weight minimization	- Elemental stresses - Nodal displacement
Talatahari, Gandomi, & Yun (2012)	2012	FA	GA, PSO, SA, ABC, CP, CSS, OC, BB-BC, ES, and GNMS	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Degertekin & Hayalioglu (2013)	2013	TLBO	HS, PSO, PSOPC, HPSO, HPSACO, ABC-AP, EHS, SAHS, CMLPSA, BB-BC, and HBB-BC	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Hasançebi, Teke, & Pekcan (2013)	2013	BI	PSO, HS, SA, ES, ACO, SGA, TS, and BB-BC	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement

Table 1. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Design Criteria
Gandomi, Talatahari, Tadbiri, & Alavi (2013)	2013	KH	GA, SA, PSO, HS, MPSO, CP, AL and GNMS	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Kaveh & Khayatazad (2013)	2013	RO	GA, ACO, PSO, BB-BC, PSOPC, HPSACO	Weight minimization	- Elemental stresses - Elemental buckling
Gholizadeh (2013)	2013	PSO, CPSO, and SCPSO	GA different variants, and SA	Size and shape optimization	- Elemental stresses - Nodal displacement
Shojaee, Arjomand, & Khatibinia (2013)	2013	IDPSO and MMA	-	Size and shape optimization	- Nodal displacement - Elemental stress
Miguel, Lopez, & Miguel (2013)	2013	FA	GA different variants	Size, shape and topology optimization	- Elemental stress - Elemental buckling - Nodal displacement - Kinematical stability
Gholizadeh & Barzegar (2013)	2013	HS, EHS, SHS	HS variants, GA, PSO, enhanced CSS	Size and shape optimization	- Natural frequency
Lu, Jan, Hung, & Hung (2013)	2013	AugPSO	PSO, and PSOPC	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Faramarzi & Afshar (2013)	2013	CA-LP	GA, HPSO	Weight minimization	- Elemental stresses - Nodal displacement
Kaveh & Mahdavi (2014)	2014	CBO discrete design variables	GA, HS, PSO, PSOPC, HPSO, and DHPSACO	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Kaveh &			GA, HS, PSO,		

Table 1. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Design Criteria
. Kaveh & Zolghadr (2014)	2014	PSO, HS, BB-BC, FA, CSS, CS, ERO, DPSO, and PSRO	-	Weight minimization	- Natural frequency
Pholdee & Bureerat (2014)	2014	GA, HS, PSO, SGA, DE, ABC, ACOR, CSS, LCA, SA, TLBO, BB-BC, FA, BPBIL, CS, CMAES, CPBIL, CSSA, ETCS, ES, EP, FWA, GSA, and BAT	-	Weight minimization	- Natural frequency
Kaveh, Sheikholeslami, Talatahari, & Keshvari-Ilkhichi (2014)	2014	CSP	GA, ACO, BB-BC, PSO, HPSACO, CSS, SAHS, HBB-BC, and CMLPSA	Weight minimization	- Elemental stresses - Nodal displacement
Hasancebi & Kazemzadeh Azad (2014)	2014	RBB-BC	PSO, ACO, HS, SA, ES, TS, SGA, and BB-BC	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Kaveh & Ghazaan (2014)	2014	ECBO	GA variants, ACO, PSO, BB-BC, ERO, and DHPSACO	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Kazemzadeh Azad & Hasancebi (2014)	2014	ESASS	GA variants, FA, ABC, and modified ABC	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Khatibinia & Naseralavi (2014)	2014	OMGSA and IGSA	GA, PSO, CSS-BBBC	Weight minimization	- Natural frequency
Kaveh & Javadi (2014)	2014	HRPSO	GA, PSO, and CSS-BBBC	Weight minimization	- Natural frequency

Table 1. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Design Criteria
Kazemzadeh Azad, Hasançebi, & Saka (2014)	2014	GSS	GA, PSO, HPSO, PSOPC,	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Camp & Farshchin (2014)	2014	MTLBO	GA variants, HS, ACO, BB-BC, HPSO, CMLPSA, HBB-BC, SAHS, and ABC-AP	Weight minimization	- Elemental stresses - Nodal displacement
Kaveh & Zolghadr (2014)	2014	DPSO	GA, PSO, enhanced CCS	Weight minimization	- Natural frequency
Gonçalves, Lopez, & Miguel (2015)	2015	SG	GA variants, FA, HRPSO, CSS, and HS	Size, shape and topology optimization	- Elemental stress - Elemental buckling - Nodal displacement - Kinematical stability - Natural frequency
Hasancebi & Kazemzadeh Azad (2015)	2015	ADS	GA variants, HS, ACO, BB-BC, ES, ABC, CMLPSA, BAT, and ESASS	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Dede & Ayvaz (2015)	2015	TLBO	GA variants, SA, ES, FA, HS, HPSO, MBA	Size and shape optimization	- Elemental stresses - Elemental buckling - Nodal displacement
Bekdaş, Nigdeli, & Yang (2015)	2015	FPA	GA, ACO, HPSO, BB-BC, CMLPSA, HBB-BC, ABC-AP, TLBO, CBO, ECBO, RO, SAHS, and CSP	Weight minimization	- Elemental stresses - Nodal displacement
Sadollah, Eskandar, Bahreininejad, & Kim (2015)	2015	WCA, MBA, and IMBA	GA variants, HS, PSO, HPSO, and DHPSACO	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement

Table 1. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Design Criteria
Kaveh & Mahdavi (2015)	2015	CBO	GA, PSO, DPSO, and CSS-BBBC	Weight minimization	- Natural frequency
Kaveh & Mahdavi (2015)	2015	2D-CBO	GA, HS, ACO, BB-BC, RO, ECBO, PSO, DPSO, CSS, CSS-BBBC, and CBO	Weight minimization	- Natural frequency
Kaveh & Mahdavi (2015)	2015	CBO-PSO	GA, HS, PSO, CSS, ECSS, CSS-BBBC,	Weight minimization	- Natural frequency
Kaveh & Ghazaan (2015)	2015	ALC-PSO, and HALC-PSO	GA, PSO, FA, CSS, and CSS-BBBC	Size and shape optimization	- Natural frequency
Kaveh, Mirzaei, & Jafarvand (2015)	2015	MCSS, and IMCSS	GA, HS, PSO, PSOPC, HPSACO, RO, ICA and DHPSACO	Size and shape optimization	- Elemental stresses - Elemental buckling - Nodal displacement
Kaveh & Bakhshpoori (2015)	2015	CS-SSM	GA, ACO, PSO, BB-BC, HBB-BC, and CS	Weight minimization	- Elemental stresses - Nodal displacement
Ho-Huu, Nguyen-Thoi, Nguyen-Thoi, & Le-Anh (2015)	2015	D-ICDE	GA variants, SA, PSO, CPSO, SCPSO,	Size and shape optimization	- Elemental stresses - Elemental buckling - Nodal displacement
Li & Ma (2015)	2015	SSO	GA, PSO, HS, PSOPC, HPSO, ABC, TLBO, and DHPSACO	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement

Table 1. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Design Criteria
Cheng, Prayogo, Wu, & Lukito (2016)	2016	HHS	GA variants, HS, PSO, HPSO, SA, BB-BC, DHP-SACO, ESASS, and ADS	Weight minimization	- Elemental stresses - Nodal displacement
Bureerat & Pholdee (2016)	2016	ADEA	HPSACO, ABC-AP, SAHS, TLBO, and CSP	Weight minimization	- Elemental stresses - Nodal displacement
Farshchin, Camp, & Maniat (2016)	2016	SBO	GA, OMGSA, ECBO, ALC-PSO, HALC-PSO, DPSO, CSS-BBBC, HRPSO, and TLBO	Weight minimization	- Natural frequency
Hosseinzadeh, Taghizadieh, & Jalili (2016)	2016	EM-MS	GA, PSO, DPSO, FA, HALC-PSO, CSS, ECSS, CSS-BBBC OMGSA	Weight minimization	- Natural frequency
Pham (2016)	2016	ANDE	DE, CSS-BBBC, TLBO, HALC-PSO,	Size and shape optimization	- Natural frequency
Farshchin, Camp, & Maniat (2016)	2016	MC-TLBO	GA variants, PSO, DPSO, HRPSO, OMGSA, CS-BBBC, and ECBO	Size and shape optimization	- Natural frequency
Savsani, Tejani, & Patel (2016)	2016	MS-TLBO	PSO, CSS, and TLBO	Weight and Topology optimization	- Elemental stress - Elemental buckling - Nodal displacement - Kinematical stability - Natural frequency

Table 1. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Design Criteria
Ho-Huu, Vo-Duy, Luu-Van, & Le-Anh (2016)	2016	DE, aDE, eDE, IDE	GA variants, PSO, OMGSA, DPSO, HRPSO, CBO, ALC-PSO, HALC-PSO and CSS-BBBC	Size and shape optimization	- Natural frequency
Mortazavi & Togan (2016)	2016	iPSO	GA variants	Size, shape and topology optimization	- Elemental stress - Elemental buckling - Nodal displacement - Kinematical stability
Kazemzadeh Azad (2017)	2017	GADS, GEBB, GMBB, GADS_EBB, GADS_MBB, GADS_EBB_MBB	ADS, MBB, and EBB	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Kaveh & Zolghadr (2017)	2017	CPA	GA, PSO, CSS, DPOS, PSRO, FA, CSS-BBBC	Size and shape optimization	- Natural frequency
Cao, Qian, Chen, & Zhu (2017)	2017	EPSO	GA variations, PSO, HPSO, MSPSO, HPSSP, EHS, SAHS, HRPSO, DPSO, FA, TLBO, MC-TLBO, PSOPC, and SA	Size and shape optimization	- Natural frequency
Baghlani, Makiabadi, & Maheri (2017)	2017	TLBO-MS	PSO, TLBO-FB, TLBO-PF, HS, HPSO, HPSACO, EHS, SAHS, MTLBO, and PSOPC	Weight minimization	- Elemental stresses - Elemental buckling - Nodal displacement
Kaveh& Ghazaan (2017)	2017	VPS	GA, PSO, and CSS-BBBC	Weight minimization	- Natural frequency

Table 1. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Design Criteria
S Savsani, Tejani, Patel, & Savsani (2017)	2017	HTS, WWO, PVS, TLBO, MHTS, MWWO, MPVS, and MTLBO	-	Weight and Topology optimization	- Elemental stress - Elemental buckling - Nodal displacement - Kinematical stability
Jalili, Kashan, & Hosseinzadeh (2017)	2017	LCA	Ga variants, PSO, CSS, ECSS, DPSO, DE, RO, OMGSA, FA, BB-BC, EHS, SAHS, TLBO, CBO, ECBO and SGA	Weight minimization	- Elemental stress - Elemental buckling - Nodal displacement - Natural frequency
Kanarachos, Griffin, & Fitzpatrick (2017)	2017	c-MFOA	GA, PSO, SA, DE, aDE, eDE, MBA, TLBO, and MC-TLBO	Size and shape optimization	- Elemental stress - Elemental buckling - Nodal displacement - Natural frequency
Krempser, Bernardino, Barbosa, & Lemonge (2017)	2017	SMDE with six following surrogate models: nearest neighbors' techniques, local linear regression, weighted local linear regression and RBF Networks	-	Weight minimization	- Elemental stress - Nodal displacement
Duarte, Lemonge, & Fonseca (2017)	2017	SSA	GA, PSO, ABC, ABC-MR, and DE	Weight minimization	- Elemental stress - Nodal displacement
Kazemzadeh Azad (2017)	2017	Incorporating SIP and UBS into ADS, MBB-BC, and EBB-BC	-	Weight minimization	- Elemental stress - Elemental buckling - Nodal displacement
Aslani (2017)	2017	MVMO, MVMO-SH	GA variants, SA, HS, HPSO, MTLBO, ROA, and BB-BC	Weight minimization	- Elemental stress - Nodal displacement

Table 1. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Design Criteria
Tejani, Savsani, Bureerat, & Patel (2018)	2018	SOS and MSOS	PSO, CSS, TLBO, and MS-TLBO	Size, shape and topology optimization	- Elemental stress - Elemental buckling - Nodal displacement - Kinematical stability
Kaveh & Zakian (2018)	2018	GWO and IGWO	GA, ACO, HS, SA, ES, FA, CS, PSOPC, BB-BC, HBB-BC, RO, CBO, HPSACO, SAHS, and TLBO	Weight minimization	- Elemental stress - Nodal displacement
Khatibinia & Yazdani (2018)	2018	MGSA and AMGSA	HS, PSO, PSOPC, HPSO, HPSACO, IHS, ABC-AP, EHS, SAHS, and TLBO	Weight minimization	- Elemental stress - Nodal displacement
Degertekin, Lamberti, & Ugur (2018)	2018	JA	GA variants, SA, ADES, CS, CMLPSA, ABC-AP, SAHS, TLBO, HPSSO, FPA, HHS-LS, HBBBC-LS, MHS, iPSO, and ICDE	Size, shape and topology optimization	- Elemental stress - Elemental buckling - Nodal displacement
Sonmez (2018)	2018	GA, ACO, PSO, ABC, GSA, FA, GWO, and JA	-	Weight minimization	- Elemental stress - Elemental buckling - Nodal displacement
Kaveh, Dadras, & Montazeran (2018)	2018	CECBO		Weight minimization	- Elemental stress - Elemental buckling - Nodal displacement
Azad, Bybordiani, Azad, & Jawad (2018)	2018	BB-BC	-	Size and shape optimization	- Elemental stress - Elemental buckling - Nodal displacement

Table 1. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Design Criteria
Jalili & Hosseinzadeh (2018)	2018	BBO-DE	HS, PSO, DPSO, PSOPC, HPSO, BB-BC, EHS, SAHS, TLBO, HPSSO, MBA, RO, CBO, ECBO, IMCSS, SSGA, MC-TLBO, HRPSO, DE, and BBO	Size and shape optimization	- Elemental stress - Elemental buckling - Nodal displacement
Ho-Huu, Nguyen-Thoi, Truong-Khac, Le-Anh, & Vo-Duy (2018)	2018	ReDE	GA, PSO, DSPO, CSS-BBBC, ALC-PSO, and HALC-PSO	Size and shape optimization	- Natural frequency
Lieu, Do, & Lee (2018)	2018	AHEFA	DE, FA, PSO, HS, CSS-BBBC, HALC-PSO, ReDE	Size and shape optimization	- Natural frequency
Cao, Qian, Zhou, & Yang (2018)	2018	Improved feasible-based constraint handling combined with HS, EHS, and SHS	PSO, HPSO, HPSACO, FA, TLBO, MC-TLBO, CPSO, SCPSO, and HHS	Weight minimization	- Natural frequency
Gandomi& Goldman (2018)	2018	P3	Modified GA, DE, RRHC, and PHBOA	Weight minimization	- Elemental stress - Elemental buckling - Nodal displacement
Carvalho (2018)	2018	CRPSO	GA, PSO, DPSO, HRPSO, and CSS	Size and shape optimization	- Natural frequency

Table 1. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Design Criteria
Baykasoglu & Baykasoglu (2019)	2019	WSA	ACO, PSO, RO, IRO, HPSO, ABC-AP, SAHS, EHS, TLBO, MSPSO, HPSSO, WEO, AMGSA, CPA, BB-BC, IGWO, CBO, ECBO, HALC-PSO, JA, FPA, and HTS	Weight minimization	- Elemental stress - Elemental buckling - Nodal displacement
Jafari, Salajegheh, & Salajegheh (2019)	2019	CA, EHO, and EHOC	PSO, MSPSO, HPSSO, SAHS, TLBO, FPA, HTS, IGWO, and EPSO	Weight minimization	- Elemental stress - Elemental buckling - Nodal displacement
Degertekin, Lamberti, & Ugur (2019)	2019	DAJA	GA variants, SA, FFA, multi-stage JA, HS, CBO, HPSO, DHP-SACO, CSS, TLBO, AFA, WCA, IMBA, HHS, aDE, eDE, and ESASS	Weight minimization	- Elemental stress - Elemental buckling - Nodal displacement
Tejani, Kumar, & Gandomi (2019)	2019	MOHTS	MOAS, MOACS, and MOSOS	Weight minimization and nodal displacement maximization	- Elemental stress
Millan-Paramo & Filho (2019)	2019	MSAA, and I-MSAA	DPSO, CSS-BBBC, CBO, VPS, MC-TLBO, ReDE, MSOS, HALC-PSO, and AHEFA	Weight minimization	- Natural frequency

Table 1. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Design Criteria
Kaveh & Mahjoubi (2019)	2019	SPO, and HSPO	GA, PSO, DPSO, CSS, ECSS, CSS-BBBC, DE, FA, NHPGA, HRPSO, ISOS, HALC-PSO, TLBO, MC-TLBO, ReDE and AHEFA	Size and shape optimization	- Natural frequency
Le, Bui, Ngo, Nguyen, & Nguyen-Xuan (2019)	2019	EM, FA, and EFA	SA, DE, aeDE, DHPSACO, HPSO, MBA, CBO, ECBO, WCA, IMBA, HHS, and BB-BC	Size and shape optimization	- Natural frequency
Liu, Zhu, Chen, & Cao (2019)	2020	Adaptive FOA with improved feasible-based constraint handling	PSO, HRPSO, SGA, BBo, EBBO, OC-GA, PGA, HS, FA, TLBO, MC-TLBO, ALC-PSO, HALC-PSO, CBO, IGSA, OMGSA, SOS, ISOS, DPSO, and VPS	Size and shape optimization	- Natural frequency
Jalili & Husseinzadeh Kashan (2019)	2019	OIO	HS, HPSO, DPO, OMGSA, HALC-PSO, HPSSO, BB-BC, EHS, SAHS, TLBO, RO, CBO, WEO, EM-MS, BBO-DE, CA	Weight minimization	- Elemental stress - Elemental buckling - Nodal displacement

Table 1. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Design Criteria
Pouriyanezhad, Rahami, & Mirhosseini (2020)	2020	ECM	GA variants, PSO, HPSO, MSPSO, MCSS, IMCSS, ABC, CA, EHO, EHOC, ECBO, ESASS, MTLBO, CSP, BB-BC, FPA, RO, WEO, WSA, JA, CS, IGWO, BAT, improved BAT, WOA, GSA, GWO, and PSO	Weight minimization	- Elemental stress - Nodal displacement

4.2. Frame optimization

Optimum design of frame structures, large-scale structures, in particular, 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. Frame structures optimization was handled based on continuous, discrete, and mixed continuous-discrete design variables. Moreover, a wide range of constraints has been defined in the previous efforts to provide the essential strength to withstand the effective loads and provide serviceability. Satisfying optimality criterion given providing stability, strength, and serviceability is a very difficult task in large scale structures. Metaheuristics, as a perfect alternative, was considered in a wide range of studies with regard to frame structures, as discussed accordingly. In this section, a detailed review of frame structures optimization is provided accordingly. Moreover, Table 2 summarized the highlights in the relevant literature.

4.2.1. Steel frame

In 1991, Balling (1991) utilized a SA algorithm for discrete optimization of 3D steel frames. In this study, the objective function was defined as the total weight minimization of an unsymmetrical six-story building. The tackled structure had a total of 156 members that classified into 11-member groups—seven-column groups and four girder groups. The constraints were defined based on AISC regulations for inters-story drift in each direction and combined stress constraints (i.e., combined tension and a combined compression). In a similar effort, May & Balling (1992) applied a filtered SA (FiSA) strategy for discrete optimization of the same frame as Balling (1991). The linearized branch and bound strategy (LB&B) was utilized for discrete optimization. A sensitivity analysis was conducted on the effect of different neighborhood sizes on the performance of the LB&B strategy. Moreover, the effect of different settings of hyperparameters of FiSA was examined through several case studies. In both studies (Balling, 1991; May & Balling, 1992), 11 groups of structural elements for columns and girders were made from wide-flange (W) shape sections available in AISC.

In 2000, Pezeshk, Camp, & Chen (2000) automated the non-linear optimum design of steel frame structures. The design procedure followed the defined requirements and available W-section elements by AISC-LRFD. In this study, different combinations of linear and non-linear analysis with considering and ignoring P-Δ effects. The positive impacts of a proposed group selections mechanism, as well as using an adaptive cross-over operator, were confirmed. P-Δ effects on the final design were found to be negligible. It was mentioned that geometrically nonlinear analysis resulted in 4% heavier structures than other cases. Sarma & Adeli, 2000) studied a fuzzy discrete multicriteria optimization (FDMCO) of steel frames. To this end, the objective function was defined as total cost minimization given three simultaneous design criteria as follows: 1- minimum material cost, 2- minimum weight, and 3- a minimum number of different section types. Four different combinations of the effective parameters of FDMCO were examined to reach the best performance.

In 2001, Toropov & Mahfouz (2001) utilized a modified GA (MGA) algorithm for discrete optimization of the total weight of steel frames. Two modifications were considered in this MGA as follows: (i) starting with a very large initial population, and (ii) the common features of the best individuals were extracted and applied to the rest of the population other than the elite. The design procedure, as well as the available sections for the structural elements, were defined in accordance with British standards. Hayalioglu (2001) employed a GA for weight minimization of moment-resisting frames based on both AISC-LRFD and AISC-ASD requirements (stress and displacements). It was claimed that fitness scaling, as well as higher crossover probability, resulted in faster convergence. LRFD-based designs were found to be 28%, 12%, and 0.7% saving in the weight in comparison with ASD-based designs for the three tackled frames. From this pattern, it was inferred that for dominant stress cases, LRFD resulted in lighter designs then ASD, while for the dominant displacement case, there is no sensible difference between them.

In 2002, Sarma & Adeli (2002) tackled life-cycle cost optimization of steel structures using fuzzy logic. Four fundamental objectives were followed during the design procedure: i- select available sections with the lowest cost, ii- select available sections with the lowest weight, iii- select the minimum number of different available sections, and iv- select available section with the minimum total perimeter length. The optimization procedure in this study was the same as Sarma & Adeli (2000). Lagaros, Papadrakakis, & Kokossalakis, (2002) enlisted several evolutionary algorithms—GA, micro GA (μGA), modified μGA (mμGA), ES, multi-membered ES (MMES), contemporary ES (CES), and adaptive ES (AES) algorithms—for structural optimization. Moreover, the sequential quadratic programming (SQP) approach was incorporated into the GA (GA-SQP) and ES (ES-SQP) algorithms for the sake of improving their performances. Two approaches were proposed to handle the sensitivity analysis as a requirement of SQP as follows: 1- Global finite difference method, and 2- Semi-analytical method. To that end, after finishing the search process using the mentioned evolutionary algorithms, SQP started the second phase to improve the best-found solution obtained in the first phase. The cross-section of each member was suggested to be I-shape defined using two design variables satisfying Eurocode 3 (1993) requirements. The performances of the following constraint handling schemes on the GA were examined through numerical simulations: static penalties, dynamic penalties (D-GA), Augmented Lagrangian method (AL-GA), and Segregated GA (S-GA). Their performances were measured using two parameters: objective values and the average level of violation.

In 2003, Liu, Burns, & Wen (2003) applied a multi-objective GA (MO-GA) to the discrete steel frame optimization. In this study, three different objectives were determined based on initial material costs, life-time seismic damage (LSD) costs, and detailing/erection complexity as measured by a diversity index. Seismic design requirements were extracted from AISC-LRFD seismic provisions and NEHRP (*Federal Emergency Management Agency. NEHRP Recommended Provisions for Seismic Regulations for New Buildings and Other Structures*, 1998) provisions. Acceleration response spectra in three hazard levels were considered (i.e., 2%, 10%, and 50% PE in 50 years). Damage state was defined in seven different levels based on the drift (i.e., none, slight, light, moderate, heavy, major, and destroyed).

In 2004, Hayalioglu & Degertekin (2004) employed a GA for the optimum design of semi-rigid connections steel frames. The best settings for different parameters of the GA, such as population size and cross-over as well as fitness scaling, were proposed. Results confirmed that using semi-rigid connections ended up with a reduction of 24% at most in the final cost rather than rigid connections. However, semi-rigid connections increased the sway of the frame between 19% and 100%. In the case of using semi-rigid column bases, a reduction of 3-25% was observed. Greiner, Emperador, & Winter (2004) studied both discrete and continuous frame optimization using evolutionary algorithms. Rebirth and auto-adaptive rebirth operators were incorporated into the utilized algorithms. This research explored both single objective (considering weight minimization) and multi-objective (simultaneous minimization of total weight and number of different cross-section types) optimizations.

In 2005, Camp, Bichon, & Stovall (2005) employed an ACO algorithm for the optimum design of steel frame based on AISC-LRFD regulations. A comparison of the results with a GA in previous studies implied that ACO was capable of finding a more optimum solution with less computational efforts. Hayalioglu & Degertekin (2005) attempted to solve the cost minimization of steel frames with semi-rigid connections and column bases using a GA. In this way, two different strategies were proposed for selecting design variables: (i) selecting columns and beams from smaller and larger height profiles, respectively; and (ii) selecting each of the columns and beams from two separate steel section lists. A comparison of the results obtained based on AISC-LRF with AISC-ASD ended up finding fewer costs using the former. The effect of stiffness of semi-rigid connections was explored through solving eight different semi-rigid connection types and semi-rigid column bases.

Yun & Kim (2005) cope with steel frame discrete optimization using a GA. To that end, second-order inelastic analysis—refined plastic hinge analysis in particular—was accounted for in the design procedure. In the refined plastic hinge analysis method, geometric nonlinearity is considered by using the stability functions of beam-column members, and the material nonlinearity is considered by using the gradual stiffness degradation model that includes the effects of residual stresses, moment redistributions by the occurrence of plastic hinges, and geometric imperfections of members. Three case studies were resolved using the proposed methodology, and the results compared to elastic-based design following the AISC-LRFD requirements, nonlinear geometric analysis, and plastic zone analysis methods. A comparison of the results indicated that elastic-based design did not show ductile behavior, while geometric nonlinear analysis and plastic zone analysis methods could carry ultimate loads and showed ductile behavior.

In 2006, Gero, García, & del Coz Díaz (2006) compared the elitist GA (EGA) with classical optimization algorithms for handling 3D steel frames. Discrete design variables governed the optimization procedure based on the available sections in the Spanish Basic Building Code (NBE EA-95).

In 2007, Degertekin (2007) compared GA and SA algorithms in dealing with geometrically nonlinear steel space frames. Stress capacity was defined based on AISC-ASD and AISC-LRFD. The numerical simulations showed that SA was successful in saving 2.3-5.6% of weights rather than GA based on the LRFD code. That was about 1.3-8% when ASD code was utilized. Moreover, the running time for GA was less than SA. In another study, Artar & Daloğlu (2018) utilized an HS algorithm for weight minimization of steel frame structures based on AISC-LRFD requirements and discrete design variables. A comparison of the results obtained by HS with GA and ACO proved the better performance of this algorithm. HS ended up to 2.7-5.0% lighter design than GA and 1.2-2.7% lighter than ACO. A low standard deviation of the results (about 3%) demonstrated the stability of the HS algorithm.

In 2009, Ali, Sellami, Cutting-Decelle, & Mangin (2009) applied a GA to the multi-stage production cost of semi-rigid steel frames. In this effort, the total cost of different stages of production was minimized. In this way, structural members and joint detailing were taken into account in the final cost estimation. Material supply, fabrication, erection, and foundation stages were involved in computing the production cost of a steel building project. The obtained results from the simulations proved that the proposed methodology decreased the final cost by around 10-25% compared to traditional designs. Moreover, it was stated that the cost of joints represented more than 20% of the optimal cost design.

In 2010, Kaveh, Farahmand Azar, Hadidi, Rezazadeh Sorochi, & Talatahari (2010) proposed an ACO algorithm as a solver to handle performance-based seismic design of steel frames using discrete design variables. Four performance levels were considered in the nonlinear analysis of the structure based on the lateral drift (i.e., operational, immediate occupancy, life safety, and collapse prevention). Moreover, two different approaches for numerical modeling and analytical process were compared as follows: (i) the refined plastic hinge analysis method, (ii) the plastic zone analysis method. The refined plastic hinge analysis method accounted for the geometric nonlinearity of a steel frame structure, the gradual plastification of member sections, and the geometric imperfection of column members. A push-over analysis was taken care of first-order elastic and second-order geometric stiffness properties. The seismic loadings were taken from four earthquake probability of 50%, 20%, 10%, and 2% in a 50-year period. The results obtained by ACO compared with a GA and confirmed the superiority of ACO over a GA.

Kaveh & Talatahari (2010a) developed an improved ACO algorithm (IACO) for discrete optimum design of frame structures. Basically, IACO worked on two phases, including global and local searches. In the first phase, a sub-optimization mechanism (SOM) based on the finite element method was incorporated into the search procedure to reduce the time by shrinking the search space. The second phase tried to optimize the solution obtained by the first phase by tweaking the design variables. Hasançebi, Erdal, & Saka (2010) utilized an adaptive HS algorithm (AdHS) to handle discrete optimization of steel frames. The obtained results were compared to the original HS algorithm as well as other previously utilized algorithms in the same case study. It was stated that AdHS outperform the HS's results significantly. Studying the effect of control parameters of AdHS revealed that it did not affect the accuracy, but the adaptation rate was changed.

Hasançebi, Çarbaş, Doğan, Erdal, & Saka (2010) provided a comparative study over the performances of seven algorithms, including GA, SA, ES, PSO, TS, ACO, and HS algorithms for handling rigid steel frame optimization. The affected loads included dead, live, snow, and wind combined based on ASCE 7-05 (*ASCE 7-05. Minimum Design Loads for Building and Other Structures.*, 2005) recommendations. Issa & Mohammad (2010) made a modification on distributed GA (DGA) by enlisting twin analogy and elitism strategy in addition to using three mutation schemes (i.e., linear, quadratic, and exponential). The mutation was found to be effective in convergence speed and finding a more optimal solution. Although all the mutation schemes were efficient in improving the performance of the presented algorithm, an exponential scheme was the most efficient strategy. Gholizadeh & Salajegheh (2010) developed an artificial intelligence-based approach for the seismic design of structures. The proposed method was based on a hybridizing PSO algorithm with an adaptive virtual sub-population (AVSP) algorithm for weight minimization. The response of structure as a necessary part of the seismic design was predicted using a hybrid approach based on adaptive neuro-fuzzy inference system (ANFIS), wavelet transforms (WT), and radial basis function (RBF) neural networks called fuzzy wavelet radial basis function (FWRBF) neural network. This proposed approach facilitated evaluating the time history response. In this study Uniform Building Code (UBC) was utilized as seismic code to select and scale ground motion time history component. Stress and displacement were supposed to control the design procedure.

Degertekin & Hayalioglu (2010) utilized the HS algorithm for steel frame optimization with semi-rigid connection and column bases. In order to evaluate the proposed model, the results were compared to rigid connection frames, and the GA was also considered for further examination. Three case studies were resolved in this study, considering eight different stiffnesses for the semi-rigid connections. HS was successful in the finding of 4.4-29.6% lighter and 2-31.8% less cost than GA, with a lower number of analyses. Furthermore, HS performed more stable than GA, with a standard deviation of less than 3%. From the minimum-weight design viewpoint, a rigid connection resulted in better designs. However, considering the total cost, semi-rigid connections were more economical.

In 2011, Liu (2011) investigated the minimum weight design of steel moment frames accounting for the progressive collapse. In this way, the alternate path method with three different analysis procedures—linear static, nonlinear static, and nonlinear dynamic—was considered according to the regulations provided by the United States Department of Defense United Facilities Criteria (UFC) Design of Buildings to Resist Progressive Collapse. Moreover, traditional seismic design without the effects of the progressive collapse was also considered as a benchmark. Four different combinations of dead, live, roof, snow loads in addition to the five-percent damped design spectral response acceleration parameter at short periods, and the effect of horizontal seismic forces. Two additional loading combinations resulted from the amplified seismic loads were considered for checking the column strength under a specific condition. Linear static design procedure resulted in the heaviest results. On the other hand, the more accurate nonlinear static and dynamic procedures ended up more optimal solutions resistance to progressive collapse but more computational efforts.

Kripakaran, Hall, & Gupta (2011) utilized a GA for the optimum design of moment-resisting steel frames. The cost of steel and connections were included in the final objective value. As the material and labor costs are location-dependent, the objective function was defined based on their ration to generalize its application. In this study, each joint could have either a fully-rigid or hinge connection. In addition to the cross-section of the elements, a binary decision making was conducted to determine connections' types. The optimization procedure was based on two phases as 1- finding the least weight solution for only considering the rigid connections, and 2- finding a trade-off between a number of rigid and hinge connections using a GA. Based on the results, it was concluded that the total cost was optimum when only a few connections were rigid. In the case of having fixed supports, a trade-off between the number of rigid connections and the total cost was observed, while for hinge supports, there not such a trade-off.

Oskouei, Fard, & Aksogan (2012) took into account the weight optimization of steel frames with semi-rigid connections using a GA. In this study, modal analysis, as well as linear and non-linear static analysis of the structures were considered. During the optimization procedure, a different level of rigidity of connections was assessed to find the most optimum case. Nine different case studies from low rise to high rise frames were simulated during the design procedure. It was indicated that the weight of structure increased by decreasing the rigidity of connections for low rise with low periods, while for medium and high-rise buildings with long periods, it was reverse. Cost-effective designs were observed for medium and high-rise buildings in the case of using semi-rigid connections and non-linear analysis, while for short buildings using rigid connections and nonlinear analysis was the case. Kaveh & Bakhshpoori (2013) concentrated on the weight minimization of steel frames using a CS algorithm. A sensitivity analysis of the optimal settings of the essential parameters of CS was conducted based on different case studies. Results declared that the displacement was controlling the design as the height of the structure got higher. CS results were better than other algorithms in most of the cases.

Kaveh & Farhoudi (2011) did a comprehensive survey on some metaheuristics (GA, PSO, ACO, and BB-BC) for layout optimization of steel frame structures. They evaluated the effect of necessary parameters of each algorithm on its performance based on a criterion called convergence factor as the average possibility of the exemplars. The design procedure is considered to be based on controlling drift, deflection, compaction, strength, stability coefficient, irregularity, and slenderness based on available standard codes (AISC Committee. Specification for Structural Steel Buildings (ANSI/AISC 360-05). American Institute of Steel Construction, Chicago-Illinois., 2005; ANSI/AISC 341-05. Seismic Provisions for Structural Steel Buildings, American Institute of Steel Construction, Chicago, Illinois 60601-1802; March 9, 2005., 2005; ASCE/SEI 7-05. Minimum Design Loads for Buildings and Other Structures. American Society of Civil Engineers., 2009; International Building Code 2006. International Code Council, INC., 2006).

Hasançebi, Bahçecioğlu, Kurç, & Saka (2011) tackled the problem of high-rise steel building weight minimization using an ES integrated parallel algorithm. Based on the results, parallel computing was found to be a time-efficient method for large scale problems. Safari, Maheri, & Maheri (2011) developed an improved multiple-deme GA (IMDGA) algorithm by proposing new crossover and mutation operators for optimum design of steel frames. The obtained results from the proposed algorithm were compared to the original GA and multiple-deme GA (MDGA) algorithms.

Kaveh, Laknejadi, & Alinejad (2012) handled a performance-based multi-objective optimization of space frames using a modified non-dominated sorting genetic algorithm (NSGA-II) by applying the DE operator (NSGA-II-DE). In this algorithm, at every generation, a population of size N (Pt) was generated using the basic NSGA-II algorithm, and another population with the same size would be generated using three selected individuals form Pt through crossover and mutation operators. The best N individuals of the combined population would be directed to the next generation. This multi-objective approach tackled the initial and life-cycle costs as two separate objectives. The structural performance was estimated by performing a push-over analysis for a structure affected by gravity and seismic loads. ASCE-7 (2009) and FEMA-273 (1997) were utilized to evaluate dead and live loads combinations. The lifecycle cost of a structure was evaluated based on lifetime seismic damage cost as a total of initial cost, the cost of damage or repair, loss of contents, injuries, and human fatality, and other economic loss caused by structural damage. The damage was defined as a percentage level of initial cost respect to the level of damage (none, slight, light, moderate, heavy, major, and destroyed). In order to decrease computational efforts, the response of structure was evaluated using a hybrid metamodel as a combination of the multi-layer perceptron and radial basis function (RBF) networks and the support vector machines.

In 2012, Doğan & Saka (2012) utilized the PSO algorithm for the optimum design of unbraced steel frames based on LRFD-AISC specifications. Toğan (2012) considered a TLBO algorithm for the optimum design of steel-framed based on AISC-LRFD. Hasançebi & Kazemzadeh Azad (2012) proposed two reformulations of the BB-BC algorithm as exponential (EBB-BC) and modified BB-BC (MBB-BC) for discrete optimum design of steel frames using W-shape sections. AISC-ASD was utilized to set the stress, displacement, geometric constraints for beams and columns at joints for constructability. Aydoğdu & Saka (2012) utilized the ACO algorithm for the minimum weight design of regular and irregular steel space frames by including the warping effect. A sensitivity analysis was conducted over different features of the ACO algorithm. Four case studies (two regulars and two irregulars) were solved using the proposed methodology with and without the warping effect. The results indicated that considering the warping effect causes a significant increase in the optimum designs of both symmetrical and asymmetrical space frames. Gholizadeh & Fattahi (2014) developed a modified PSO (MPSO) for the optimum design of tall steel buildings. This MPSO algorithm worked based on using PSO with a multi-stage strategy where the output of each stage would be the initial population for its next stage. Kaveh & Talatahari (2012b) utilized the CSS algorithm for the optimum design of frame structures. The fundamental regulations of design procedure were compatible with AISC-LRFD specifications for stress and displacement.

In 2013, Phan, Lim, Sha, Siew et al. (2013) concentrated on the weight minimization of cold-formed steel portal frames using a GA. The trial designs were constructed using three design variables as sections size, spacing, and pitch of the frames. Two different types of frames were studied as a rigid-jointed cold-formed portal frame with and without knee braces. Constraints were defined for columns and rafters to check combined axial compression and bending, distortional buckling, and combined bending and shear.

Knee braces were checked against compression and tension. Numerical simulations declared that considering topological variations during the optimization procedure resulted in more optimal solutions. Moreover, incorporating braces into the frames ended up decrease in the final cost.

Kazemzadeh Azad, Hasançebi, & Kazemzadeh Azad (2013) utilized an upper bound strategy (UBS) for optimum design of steel frames by metaheuristic algorithms. To that end, they employed a 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. Structural analyses were handled using SAP2000 software in conjunction with MATLAB. 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, Khalili, & Alavizadeh (2013) employed accelerated PSO (APSO) for optimum design of frame structures based on AISC-LRFD requirements. Yang, Bletzinger, Zhang, & Zhou (2013) developed a parallel modified guaranteed converged PSO algorithm (PMGCPSO) for size and topology optimization of frame structures. During the topology optimization procedure, the main objective was finding the best layout for bracing. The obtained results by PMGCPSO were compared to the covariance matrix adaptation ES (CMA-ES) algorithm.

Gong, Xue, & Xu (2013) delivered a multi-objective optimization of eccentrically braced steel frames (EBF) using a multi-objective GA (MOGA). The objective functions in this study were cost minimization, seismic input energy E_i to the seismic-force-resisting system (SFRS) minimization, and the hysteretic energy of fuse members maximization. The analyzing procedure was mainly based on nonlinear response history analysis (NRH) to capture both dynamic and inelastic behavior of a structure. The constraints defined for checking the model validity were: 1- the plastic deformation on fuse members, 2- the plastic deformation constraints on non-fuse members, and 3- inter-story drift constraints. The proposed procedure was applied to the design of an EBF frame from a 3-story space office building with a symmetric plan located in Vancouver, British Columbia, Canada. In this three-bay three-story EBF frame, all the columns were pinned-supported. Three ground motions were adopted from PEER (2008) in this research to find average values of structural response. Kaveh & Zakian (2013) explored the application of two metaheuristic algorithms—CSS and improved HS (IHS)—for optimum design of steel frames under seismic loads. Structural analysis was conducted in two phases as follows: 1- performing a time history analysis with relative lateral displacement, and 2- performing a simultaneous dynamic–static analysis with relative displacement and stress constraints. The proposed methodology was evaluated through solving four frame structures affected by three earthquake time-history records (i.e., El Centro (N-S component, 1940), Kobe (090 component, 1995), and Tabas (LN component, 1978)).

In 2014, Hasançebi & Carbas (2014) selected the BAT algorithm for discrete size optimization of steel frames based on AISC-ASD. The authors did extensive research on the parameter setting of the BAT algorithm in this paper and indicated the impact of each parameter as well as the best parameter setting. A comparison of the results in this study with other previous efforts proved the efficiency of their tackled algorithm for handling frame optimization problem. Murren & Khandelwal (2014) tackled steel frame optimization using a design-driven HS (DDHS) algorithm. DDHS used a more intelligent mutation operator which considered available information from previous solutions as well as parameter-specific search to explore the solution space. The optimization procedure was based on grouped discrete design variables selected from W-shape sections subject to stress and drift related constraints. DDHS was found to be efficient in terms of accuracy, computational efforts, and optimality of the final solutions when it was compared to other solvers.

Yassami & Ashtari (2015a) utilized a fuzzy GA (FGA) for weight optimization of steel frames with semi-rigid connections. Four types of semi-rigid connections based on different rotational stiffness values, in addition to a rigid connection, were analyzed using the proposed FGA and a simple GA. The proposed FGA was proved to be better than GA in finding more optimal solutions with faster convergence. Yassami & Ashtari (2015b) studied the weight minimization of steel frames with semi-rigid connections using the same strategy as Yassami & Ashtari (2015a) for design procedure. To that end, three optimization algorithms we selected as simple GA, FGA, and ABC. Kaveh & Nasrollahi (2014) utilized the CSS algorithm for the performance-based seismic design of steel frames. In this study, the design procedure was based on a push-over analysis using a semi-rigid connection concept. Two moment frames affected by dead, live, and earthquake loads were optimized using CSS and compared to GA and ACO. For seismic analysis, spectral acceleration was evaluated based on four performance levels as operational, immediate occupancy, life safety, and collapse prevention based on the probability of an earthquake happening within 50 years. A comparison of the results obtained by the explored algorithms indicated that CSS outperformed GA and ACO by finding lower weights.

Maheri & Narimani (2014) used an enhanced HS algorithm (EHS) based on altering the updating phase of the HS algorithm for the minimum weight design of steel moment frames. Saadat, Camp, & Pezeshk (2014)] concentrated on the performance-based optimization of structures based on a multi-objective approach. In this way, a MOGA was considered to minimize the combination of the present value of the total economic cost (PC_t^T) and expected annual social loss (EASL). The design procedure was based on inelastic time history analysis considering different levels of earthquake hazard. The numerical simulations were conducted for two locations in the United States including, Memphis and Los Angeles. The constraints were defined considering two hazard levels for collapse prevention and immediate occupancy in addition to the AISC specifications for strong column-weak beam criteria. A FEMA-SAC structure was considered for numerical simulation and model validation (FEMA 355C, 2000). Discrete design variables were considered as two columns and three beams selected from W-shape sections. Kaveh, Bakhshpoori, & Azimi (2015) tried the CS algorithm for seismic weight minimization of space steel frames. Seismic analysis of the structures was conducted through two different approaches based on equivalent static and response spectral analyses for the first two cases and spectral response analysis for the third case. The obtained results using the proposed algorithm were compared to ES, SA, and TS algorithms.

In 2015, Alberdi & Khandelwal (2015) did a comparative study on the performance of six metaheuristic techniques—ACO, GA, HS, PSO, SA, and TS—and their three modified versions—DDHS, AHS, and iSA—for weight minimization of steel frames. The efficiency of utilized algorithms was assessed in terms of convergence consistency regardless of the variable space and irrespective of the initial trials. Based on the results of simulations, DDHS and TS were the best solvers in this case study. Gholizadeh & Poorhoseini (2015) applied a modified dolphin echolocation optimization (MDEO) algorithm for the optimization of steel frames. This modified algorithm was based on using one-dimensional Gauss chaotic maps for determining the step locations. The performance of the proposed algorithm was examined through a comparison with the original dolphin echolocation (DEO) algorithm in addition to some other algorithms applied to the same examples previously. Moreover, a sensitivity analysis of an effective parameter in the MDEO algorithm called power was conducted to reach its best performance. The results approved the better performance of MDEO thanks to finding lighter designs.

Alberdi, Murren, & Khandelwal (2015) concentrated on topology optimization of connections in steel moment frames. In this way, four optimization algorithms—GA, HS, ACO, and TS—were considered to optimize both member section and connections rigidity. As a result of two available connections at two ends of each beam (pinned and moment-connected), four different types of beams were available based on the connections. The objective function was defined in terms of material cost, in addition to the connections derived costs. The first example was resolved under different assumptions, such as considering fixed and variable connection topology, along with solving the problem with and without constructability constraints. Kazemzadeh Azad & Hasançebi (2015) tackled the optimum design of steel frames with discrete design variables using a design-driven heuristic approach called the guided stochastic search (GSS) technique. The applied constraints into the design procedure were strength and displacement based on AISC-LRFD. Comparison of the results obtained by GSS with some other algorithms—upper bound strategy (UBS), UBS combined with BB-BC (UBB-BC), UBS combined with modified and exponential BB-BC (UMBB-BC and UEBB-BC), and UBS combined with PSO (UPSO)—indicated its promising performance thanks to finding more optimal solutions with less computational efforts.

Hadidi & Rafiee (2015) hybridized HS and BB-BC algorithm (HS-BB-BC) to tackle the problem of frame weight minimization considering the optimal arrangement of semi-rigid connections types. In this way, eight different semi-rigid connections were proposed based on the rotational stiffness. The objective function was defined as the total cost of materials in addition to the surcharge due to connection types. In this study, a non-linear structural analysis was accomplished based on the non-linear moment-rotation behavior of connections and P-Δ effects. Numerical simulations declared that the proposed HS-BB-BC was successful in finding better solutions than the original HS and BB-BC algorithms with a better convergence rate. Talatahari, Gandomi, Yang, & Deb (2015) studied the optimum design of frame structures using a two-stage optimization algorithm based on the eagle strategy and DE (ES-DE). The proposed ES-DE outperformed the original DE, and its performance was comparable to other previously utilized algorithms.

In 2016, Carbas (2016) proposed an enhanced FA (EFA) for steel frame optimization. The design procedure followed LRFD-AISC regulations using discrete design variables. In this way, several constraints were incorporated into the design process to check elements stress capacities, maximum displacement, geometrical constraints for beam-column connections, and columns related constraints to prevent soft story. Based on the results, EFA was successful in finding more optimal solutions than the FA. In another effort, Carbas (2017) utilized the BBO algorithm for the minimum weight design of frame structures with the same strategy as Carbas (2016). The proposed approach was applied to the optimum design of two real-size steel space frames. Comparison of BBO with some other algorithms which were tried previously in similar cases studies revealed its superiority and success to find better solutions.

Gholizadeh & Poorhoseini (2016) utilized an improved DEO (IDEO) algorithm for seismic performance-based layout optimization of braced frames. The proposed improvement on the algorithm was using the chaos theory for modifying the accumulative fitness equation of standard DEO. To that end, three performance levels (i.e., immediate occupancy, life safety, and collapse prevention) were considered for seismic hazard analysis. Therefore, the basic seismic loading was represented by three earthquake level corresponding to 20, 10, and 2% probability of exceeding in a 50-year period. In this study, cross-sections of structural elements as well as placement of the X-bracing in the frame were supposed to be design variables. The design procedure of the structure was conducted using nonlinear pushover analysis. In the former type, the design procedure was linear, and geometry constraints were ignored to be uniform with the original study. In the latter, the tackled frames were solved based on two strategies as (i) size optimization of frames wit fixed configuration of braces, and (ii) layout optimization of braces. During the design procedure, a sensitivity analysis over the variation of one of the most effective parameters of Ide named power was conducted to catch its best performance.

Aydoğdu, Akın, & Saka (2016) concentrated on the optimization of steel space frames using an ABC algorithm with levy flight distribution (LFABC). The performance of the proposed algorithm was compared with ABC, ACO, and dynamic HS (DHS). Kaveh & BolandGerami (2017) proposed a cascade optimization method for the optimum design of large-scale space steel frames. To this end, the ECBO algorithm was utilized successively to handle every single case study. Papavasileiou & Charmpis (2016) utilized ES for optimum cost and braces topology design of earthquake-resisting multi-story steel-column composite structures. The design procedure was based on discrete optimization with I-shaped sections fully encased in concrete for the columns, I-shaped sections for beams, and L-shaped sections braces. The objective function was the total cost of steel and column that satisfied the requirements defined by Eurocodes 3 and 4. Nonlinear pushover and eigenvalue analyses were considered for structural analysis. The constraints were defined to guarantee enough stress capacity, prevent unacceptable displacement due to earthquake, and preventing undesirable long-period buildings.

Carraro, Lopez, & Miguel (2017) utilized a search group algorithm (SGAO) for the minimum weight design of frame structures based on AISC-LRFD. Daloglu, Artar, Özgan, & Karakas (2016) considered the effect of soil-structure interaction in steel frame optimization. In this way, the minimum-weight design of frame structures located on elastic foundations was the subject of the study. The soil of the foundation was specified using three parameters (i.e., moduli of subgrade reaction, soil shear parameter, and vertical deformation profile within subsoil). Prendes-Gero, Álvarez-Fernández, López-Gayarre, Drouet, & Junco (2016) utilized a GA developed from the Eugenics Evolutionary theory (GAET) for the cost minimization of steel frames. The final cost resulted from the cost elements and connections. During the design procedure, columns were selected from HEB sections, and the beam was selected form I sections. Three case studies were proposed to examine the efficiency of the proposed algorithm. In these examples, the effects of different parameter settings of the algorithm, number of sub-beam-elements, and different optimization processes (elitist strategy, steady-state replacement, roulette wheel, tournament selection, and Eugenics theory) were examined.

In 2017, Gholizadeh, Davoudi, & Fattahi (2017) utilized an enhanced MFO algorithm (EMFO) for the optimum design of steel frames. The applied modification was related to position updating using the best information obtained from the search agents during the optimization process. Moreover, a mutation operator was added to this algorithm. Kaveh, Ghafari, & Gholipour (2017b) studied seismic design optimization of steel moment frames with connection types arrangement considerations. To that end, in addition to the cross-section of elements, connection types (simple or rigid) were considered as the design variables. The objective function was defined in terms of material and connection costs. The optimization procedure was accomplished using the PSO and ECBO algorithms. An ANN-based approach was proposed to predict structural seismic response for seismic time-history analysis. ECBO was found to be much better than PSO in solving the tackled problem. Moreover, considering the connection types in the optimization procedure resulted in more efficient designs.

Gholizadeh & Baghchevan (2017) tackled multi-objective optimization of the performance-based design of steel moment-resisting frames. To this end, a chaotic multi-objective firefly algorithm (CMOFA) was utilized to minimize the total weight of the structure, while inter-story drift was maximized subject to the serviceability and ultimate limit-state constraints. Three different steel frames were considered to endure dead, live, and earthquake loads considering three performance levels (i.e., immediate occupancy, life safety, and collapse prevention). Maheri, Shokrian, & Narimani (2017) employed an enhanced honey bee mating optimization (EHBMO) algorithm for the optimum design of steel frames. This modification defined a distance factor that gave credence to less feasible solutions to broaden the search space. Kaveh, Ghafari, & Gholipour (2017a) tackled seismic optimization of 3D steel frames using nine different algorithms as SA, PSO, ABC, WOA, GWO, HS, CBO, ECBO, and invasive weed optimization (IWO). Three different types of lateral resisting steel moment frames were studies according to the AISC-LRFD design criteria as follows: ordinary moment frame (OMF), intermediate moment frame (IMF), and special moment frame (SMF). The optimization procedure was based on the Response Spectrum Analysis (RSA) approach. Optimization results demonstrated that OMF resulted in lighter designs in most of the cases. On the other hand, IMF was not a good choice for structures with box shape columns. HS, PSO and CBO performed better than other techniques.

In 2018, Gholizadeh & Ebadijalal (2018) utilized the center of mass optimization (CMO) algorithm for weight and topology optimization of steel braced frames. Topology optimization of the frames dealt with finding the best configuration of X- and diagonal-bracing system in a given steel frame. In this study, in addition to design variables for selection cross-section of the elements, four different options were defined for the brace configuration in each bay. The design procedure was based on nonlinear time history analysis considering three performance levels as immediate occupancy, life safety, and collapse prevention. Gholizadeh & Milany (2018) developed an improved firework algorithm (IFWA) for discrete optimization of steel structures. The obtained results were compared to the original algorithm (FWA) to assess the efficiency of the proposed modifications. Results demonstrated that IFWA outperformed FWA, and its results were also competitive with other previously utilized algorithms. Farshchin, Maniat, Camp, & Pezeshk, (2018) a school-based optimization (SBO) algorithm for optimum design of steel frames considering AISC-LRFD regulations. Artar & Daloğlu (2018) studied the optimum weight design of steel space frames with semi-rigid connections using an HS algorithm and a GA. In addition to a rigid connection, six types of semi-rigid connections based on different rotational stiffness were considered within the design procedure.

In 2019, Bybordiani & 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. A 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. Zakian (2019) tackled steel moment-resisting frames considering natural frequency constraints using five optimization algorithms as follows: PSO, CSS, TLBO, GWO, and improved GWO (IGWO). To this end, the natural frequency of structure was obtained using eigenvalue analysis. The results declared that TLBO, IGWO, and PSO were the best solvers. Hassanzadeh & Gholizadeh (2019) accounted for collapse-performance-aided optimization of steel concentrically braced frame (SCBF) using the CMO algorithm. To this end, three major steps were proposed as follows: 1- size and topology optimization based on seismic performance-based analysis, 2- generating fragility curves for the optimal solutions using the incremental dynamic analysis, and 3- fixed and optimized braces configurations were compared in terms of minimum weight and collapse capacity. The performance-based analysis was conducted based on three hazard levels—immediate occupancy, life safety, and collapse prevention. The design variables were defined as the cross-section and brace placement in the frame. Based on the results, it was found that the topology optimization resulted in more optimal solutions with considerably better collapse safety.

In 2020, Kaveh, Biabani Hamedani, Milad Hosseini, & Bakhshpoori (2020) utilized several optimization algorithms—ABC, BB-BC, cyclical parthenogenesis algorithm (CPA), CS, thermal exchange optimization (TEO), water evaporation Optimization algorithm (WEOA), and TLBO algorithms—to solve steel frame optimization problems. In terms of more fit solutions, WEO, CS, and TEO proved to be the best optimizer while the convergence speed was better for TEO, TLBO, and WEO.

4.2.2. Concrete frame

In 2008, Paya, Yepes, González-Vidosa, & Hospitaler (2008) considered multi-objective optimization of concrete frames using a SA algorithm (MO-SA) based on four different objectives as follows: the economic cost, the constructability, the environmental impact, and the overall safety of RC framed structures. The Spanish code NBE AE-88 (Fomento, 1988) for concrete structures governed the design procedure. The trade-off between all the objectives was explored through a sensitivity analysis. Paya-Zaforteza, Yepes, Hospitaler, & González-Vidosa (2009) utilized a SA algorithm for the optimization of a reinforcement concrete (RC) frame. To this end, SA dealt with minimizing CO2 emissions and economic costs. The design procedure was controlled using the Spanish code for concrete structures (Fomento, 1998). The effects of the number of design variables on the CPU time and the number of floors on CO2 emission was explored through a sensitivity analysis. Moreover, the tradeoff between CO2 and the final cost was observed. Results declared that embedded emissions and costs are highly correlated. The lowest CO2 emission was only 2.77% more expensive than the most optimum cost-based solution. On the other hand, the most cost-effective design caused a 3.8% increase in CO2 emissions.

Camp & Huq (2013) tackled CO2 and Cost optimization of RC frames using a BB-BC algorithm. The design procedure was based on the American Concrete Institute (ACI) specifications. Discrete optimization is based on the geometry of beams and columns defined by width and height along with steel rebars areas defined by the number and size of bars. Many constraints were defined to control beam elements' validity following stress, serviceability, and geometrical requirements. The sufficiency of the columns for withstanding the combined effects of axial force and bending moments was checked through some constraints. Results declared that BB-BC was efficient in handling the tackled problems. A comparison of the results considering the cost and CO2 emission demonstrated that the best solution by CO2 minimization might be slightly more costly.

Gharehbaghi & Fadaee (2012) proposed an automated procedure to design optimization of RC structures by optimizing a three-bay eighteen-story RC frame using particle swarm optimization (PSO) algorithm. The construction cost was considered the objective function, and constraints were conformed to the ACI318-08 code and standard 2800-code recommendations as primary allowable section conditions, capacity criteria, and seismic. The results showed that a design candidate could be achieved associated with the minimum construction cost that conforms to the standard code provisions by application of an automated design process. Khatibinia, Salajegheh, Salajegheh, & Fadaee (2012) applied a discrete gravitational search algorithm (DGSA) and a metamodelling framework for reliability-based design optimization (RBDO) of reinforced concrete frames. In this study, a metamodel based on a wavelet weighted least squares support vector machine (WWLS-SVM) and the standard GSA were considered to reduce the computational effort. Furthermore, the kernel function of WLS-SVM is replaced with a cosine Gaussian Morlet wavelet function to improve the performance generality of WLS-SVM. Their results showed that the metamodel's prediction performance is influenced by selecting its kernel function and WWLS-SVM parameters. The numerical results of training and testing the metamodel also showed that the metamodel's performance generality is higher than that of WLS-SVM. Gharehbaghi & Khatibinia (2015) tackled RC structures' optimal seismic design by considering a hybrid particle swarm optimization algorithm and an intelligent regression model, subjected to several time-history earthquake loads. The proposed IRM consists of three components: SA, K-means clustering approach, and WWLS-SVM.

In 2016, Yazdani, Khatibinia, Gharehbaghi, & Hatami (2016) used a modified discrete gravitational search algorithm (MDGSA) for the sum of construction and repair costs minimization of RC frames. The utilized algorithm's efficiency was assessed against the original GSA through a nine-story RC building's performance-based design subject to both probabilistic and deterministic constraints. The metamodel was used to predict the structure's seismic response based on the weighted least squares support vector machine. Annual probabilities of nonperformance were also selected as the probabilistic constraints. In addition, in the dynamic finite element analysis of the soil-structure system, nonlinear soil-structure interaction effects were taken into account. Gharehbaghi, Moustafa, & Salajegheh (2016) also applied Particle Swarm Optimization (PSO) algorithm to minimize the construction cost of three low- to high-rise RC frame structures under earthquake loads with and without considering strong column-weak beam (SCWB) constraint. In this study, an intelligent pre-processing method was considered using a Tree Classification Method (TCM) and a nonlinear optimization technique in which the TCM automatically creates sections database and assigns sections to structural members.

Gharehbaghi (2017) minimized the construction cost of reinforced concrete frame structures by applying a PSO algorithm binary model. Due to earthquake excitations, a uniform damage distribution was considered over the structure's height in this study. The allowable degree of damage was defined based on the concept of the global collapse mechanism. They compared uniform damage-based optimum seismic design and the strength-based optimum seismic design. The results showed that the uniform damage-based method offers a design that will suffer less damage under severe earthquakes.

Table 2. Review of the application of metaheuristic algorithms to frame structures.

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Balling (1991)	1991	SA	-	Weight minimization with discrete design variables	1- Inter-story drift 2- Elemental stress	1- An asymmetrical six-story 3D building frame was analyzed
May & Balling (1992)	1992	FiSA	SA	Weight minimization with discrete design variables	1- Inter-story drift 2- Elemental stress	1- An asymmetrical six-story 3D building frame was analyzed
Pezeshk, Camp, & Chen (2000)	2000	GA	-	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement 3- Interaction formula of the AISC-LRFD	1- Three case studies (i.e., two different loading combinations of 2b-3s frames in addition to a 1b-10s frame) were considered 2- Example solved for three different cases: (i) linear analysis with no P-Δ effect, (ii) linear analysis with P-Δ effect, and (iii) geometrically non-linear analysis with P-Δ effect
Sarma & Adeli (2000)	2000	FDMCO	-	1- minimum material cost, 2- minimum weight, and 3- minimum number of different section types. Considering continuous design variables	1- Displacement 2- Elemental stress	1- 36-story steel space moment resisting frame structure
Toropov & Mahfouz (2001)	2001	MGA	-	Weight minimization with discrete design variables	1- Elemental stress 2- Buckling 3- Serviceability	1- Two numerical examples were tackled as: 5b-5s, and 4b-10s 2- Each structure was subjected to eight different combinations of dead, live and wind loads

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Hayalioglu (2001)	2001	GA	-	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement	1- Three space frame structures were considered as follows: 1-story 8-member, 4-story 84-member, and 10-story 130-member 2- Each structure was subjected to four combinations of dead, live, roof, and wind loads.
Sarma & Adeli (2002)	2002	FDMCO	-	1- minimum material cost, 2- minimum weight, 3- minimum number of different section types, and 4- minimum total perimeter length. Considering continuous design variables	1- Elemental stress 2- Displacement	1- 36-story steel space moment resisting frame structure
Lagaros, Papadrakakis, & Kokossalakis (2002)	2002	GA, μGA, mμGA, ES, MMES, CES, AES, SQP, GA-SQP, ES-SQP, AL-GA-ES, and ES-AL-GA	-	Weight minimization	1- Inter-story drift 2- Elemental stress 3- Displacement	1- Two space-frame were analyzed using the proposed algorithms as follows: 2b-6s irregular frame, and 3b-20s regular frame

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Liu, Burns, & Wen (2003)	2003	MO-GA	-	1- initial material costs 2- lifetime seismic damage (LSD) costs detailing/erection complexity as measured by a diversity index	1- annual fatality rate 2- allowable drift 3- soft story 4- Elemental stress 5- Strong-column-weak-beam mechanism 6- Buckling 7- Axial force-bending moment interaction	1- A Five-story steel moment-resisting frame office building located in downtown Los Angeles area was considered 2- Different load combination from dead, live, earthquake and wind were considered 3- Three hazard level were considered in the analyzing procedure
Hayalioglu & Degertekin (2004)	2004	GA	-	Minimum total cost as result of elements' costs and connections' costs	1- Elemental stress 2- Displacement 3- Cross sections geometry requirements	1- Two numerical examples were solved as follows: 1- 2b-5s, and 1b-10s 2- A combination of vertical and horizontal loads was applied to each case study 3- *P-Δ* effect was considered during the analysis
Greiner, Emperador, & Winter (2004)	2004	Evolutionary algorithms	-	1- Total weight minimization as single objective Simultaneous total weight minimization and different number of cross-section types as multi-objective	1- Elemental stress 2- Displacement	Three frame cases were analyzed in this study as: 5b-5s, 4b-5s, and 3b-5s
Camp, Bichon, & Stovall (2005)	2005	ACO	GA	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement 3- The interaction formulas of the LRFD specification	1- Three numerical case studies were resolved in this study as follows: 2b-3s, 1b-10s, and 3b-24s. 2- The tackled frames were subjected to both vertical and horizontal loads

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Hayalioglu & Degertekin (2005)	2005	GA	-	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement 3- Geometrical limitations for selecting	1- Three case studies were considered in this study as: 1b-9s, 3b-7s, and 4b-10s 2- Semi-rigid connections and column bases were considered 3- P-Δ effect was incorporated into the design procedure 4- Four different types of loads were employed as dead, live, roof, and wind loads
Yun & Kim (2005)	2005	GA	-	2- Weight minimization with discrete design variables	1- Load-carrying capacity 2- Serviceability 3- Ductility 4- Constructability	1- Model validation was conducted through four case studies as: 1b-3s, 2b-3s frame (type I), 2b-3s (type II), and 3b-2s frames 2- Different combinations of dead, live, snow and wind loads were applied to the structures.
Gero, García, & del Coz Díaz (2006)	2006	EGA	-	Weight minimization with discrete design variables	Not reported	1- Two 3D structures were handled using the proposed algorithm as: a portal frame structure and a three-floor steel building. 2- Two different load combinations were applied to the models as: (i) weight of structure itself, snow and wind loads for portal frame, (ii) weight of structure itself and wind load for steel building.

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Degertekin (2007)	2007	SA	GA	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement 3- Inter-storey drift 4- Columns' sizes	Three case studies were considered in this research as follows: (i) 1-storey eight-member space frame, (ii) 2-storey 26-member space frame, and (iii) 4-storey 84-memebr space frame.
Degertekin (2007)	2007	HS	GA and ACO	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement 3- The interaction formulas of the LRFD specification	1- Three case studies were considered in this study as follows: (i) 2b-3s frame, (ii) 1b-10s frame, and (iii) 3b-24s frame. 2- The first two cases affected by both vertical and horizontal loads and the third one was affected by vertical loads
Paya, Yepes, González-Vidosa, & Hospitaler (2008)	2008	MO-SA	-	1- The economic cost 2- The constructability 3- The environmental impact 4- The overall safety of RC framed structures	1- Elemental stress 2- Deflection	1- The performance of the proposed algorithm examined through a 2b-4s frame 2- 48 combinations of six following different loading cases were applied to the structure: permanent loads, live loading in every other span and the complementary, live loading in all spans, and wind in both directions.
Bel Hadj Ali, Sellami, Cutting-Decelle, & Mangin (2009)	2009	GA	-	Total cost as a result of material cost, fabrication cost, erection cost, and foundation cost	1- Elemental stress 2- Deflection	1- Three different case studies were proposed for model verification: (i) 3b-2s frame, (ii) 3b-3s, (iii) 3b-10s 2- Each frame was affected by vertical and horizontal loads

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Paya, Yepes, Hospitaler, & González-Vidosa (2009)	2009	SA	-	Total cost and CO_2 emission	1- Elemental stress 2- Deflection	The proposed methodology was applied to sex model as: 2b-2s, 2b-4s, 2b-6s, 2b-8s, 3b-4s, and 4b-4s
Kaveh, Farahmand Azar, Hadidi, Rezazadeh Sorochi, & Talatahari (2010)	2010	ACO	GA	Weight minimization with discrete design variables	Lateral deflection of building	Two numerical examples were resolved using the proposed methodology as follows: (i) 4b-3s steel frame, and (ii) 5b-9s steel frame
Kaveh & Talatahari (2010)	2010	IACO	GA, ACO, and HS	Weight minimization with discrete design variables	1- Elemental Stress 2- Lateral displacement 3- Inter-story displacement	1- Three numerical case studies were resolved using the proposed algorithm as follows: (i) 1b-8s, (ii) 1b-10s, and (iii) 3b-24s 2- All the case studies were affected by vertical and horizontal loads
Hasançebi, Erdal, & Saka (2010)	2010	AdHS	GA, TS, ACO, PSO, and HS	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement	1- Two numerical case studies were considered in this study as: (i) a braced asymmetrical 3b-20s steel frame, and (ii) a space frame structure constituted by five 6b-8s and seven 4b-8s frames. 2- The applied loads were resulted from dead, live, snow and wind loads.
Hasançebi, Çarbaş, Doğan, Erdal, & Saka (2010)	2010	GA, PSO, HS, ES, TS, ACO, and SA	-	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement 3- Geometrical constraints for cross sections	1- Three case studies were considered in study as follows: (i) a 224-member 3-bay 24-storey braced frame, (ii) a 325-member space frame, and (iii) a 568-meber space frame 2- The tackled structures were affected by

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Issa & Mohammad (2010)	2010	MDGA	GA	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement	Three numerical case studies were solved in this study as follows: a pitched-roof steel portal frame with gravitational load, one-bay three-storey frame affected by gravity, and a pitched-roof steel portal frame with lateral loads
Gholizadeh & Salajegheh (2010)	2010	PSO, AVSP, PSO-AVSP	-	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement	1- A 10-stroey moment resistant frame was considered for model evaluation 2- UBC code was considered for seismic analysis 3- FWRBF method was responsible to evaluate the response of structure
Degertekin & Hayalioglu (2010)	2010	HS	GA	Cost minimization with discrete design variables	1- Elemental Stress 2- Displacement 3- Size for beams and columns	1- Three numerical case studies were considered for model assessment as (i) 1b-9s, (ii) 3b-7s, (iii) 4b-10s 2- The tackled case studies were affected by dead, live, roof, and wind loads
Liu (2011)	2011	GA	-	Weight minimization with discrete design variables	Not reported	1- A 3b-9s steel moment frame was designed by several analysis strategies 2- Four load combinations of dead, live, roof, snow loads in addition to seismic loading were applied to the structure. 3- Two additional load combinations were added under the specific conditions.

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Kripakaran, Hall, & Gupta (2011)	2011	GA	-	Cost minimization with discrete design variables	1- Elemental Stress 2- Displacement	1- A 5b-5s frame was considered for model evaluation 2- Different combinations of dead, live, roof, and wind loads were considered based on AISC-LRFD
Oskouei, Fard, & Aksogan (2011)	2011	GA	-	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement Number and locations of the plastic hinges	1- Nine different case studies were considered as (1bay, 2-bay and 3-bay) 3-storey, (1-bay, 2-bay and 3-bay) 6-storey, and (1-bay, 2-bay and 3-bay) 9-storey 2- All the cases were affected by dead, live and seismic loads and analyzed by linear and nonlinear static analysis considering rigid and semi-rigid connections
Kaveh & Bakhshpoori (2011)	2011	CS	PSO, ACO, HS, ICA, and HBB-BC	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement	Three case studies were analyzed as follows: 1-bay 10-strory affected by horizontal and vertical loads, 3b-15s affected by horizontal loads, and 3b-24s affected by horizontal loads
Kaveh & Farhoudi (2011)	2011	GA, ACO, PSO, and BB-BC	-	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement 3- Stability 4- Compactness Irregularity	1- Three 5-bay frames (i.e., 3-storey, 5-storey, and 10-storey) were analyzed in this study 2- All the case studies were affected by dead, live and earthquake loads

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Hasançebi, Bahçecioğlu, Kurç, & Saka (2011)	2011	Parallel strategy of ES	-	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement 3- Geometric compatibility between beam and column at the rigid joints	Three large scale space frames were analyzed as follows 1040-meber with 60-member group, 3590-meber with 109-member group, and 7648-meber with 198-member group
Safari, Maheri, & Maheri (2011)	2011	MDGA and IMDGA	GA and TS	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement 3- Constructability	1- Two steel moment frames were solved using the proposed algorithms as follows: 3b-3s steel frame and 5b-22s special steel frame 2- Six combination of dead, live, snow and horizontal earthquake were applied to the proposed case studies
Kaveh, Laknejadi, & Alinejad (2012)	2012	NSGA-II-DE	-	Multi-objective optimization with minimizing two following objectives: 1- initial cost, and 2- life-cycle cost	1- Displacement 2- Strong-column-weak-beam mechanism	1- Two numerical examples were considered for model validation as follows: (i)- a 2D 5b-10s moment-resisting steel frame, and (ii)- a 3D 20-storey braced frame with 416 joints and 1,040 members 2- The tackled structures were subjected to push-over analysis as a result of seismic loading as well as dead and live gravity loads

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Dogan & Saka (2012)	2012	PSO	GA, HS, and SA	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement 3- Constructability	1- Three numerical case studies were tackled in this study as: (i) 2b-6s, (ii) 1b-10s, and (iii) 3b-15s steel frames. 2- All the cases were subjected to both vertical and horizontal loads, simultaneously.
Togan (2012)	2012	TLBO	GA, ACO, HS, and IACO	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement	Three case studies were solved in this study as follows: (i) 2b-3s frame affected by horizontal and vertical loads, (ii) 1b-10s frame affected by vertical and horizontal loads, and (iii) 3b-24s frame affected by horizontal loads
Hasancebi & Azad (2012)	2012	BB-BC, EBB-BC, and MBB-BC	HS, AHS, TS, and iSA	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement 3- Constructability	1- Two numerical case studies were resolved as 132-member unbraced steel frame and 209-member industrial factory building 2- The first case was affected by gravity and earthquake loads, and the second case was affected by six combinations of dead, live and roof loads
Gharehbaghi & Fadaee (2012)	2012	PSO	-	Cost minimization	1- steel ratio 2- flexural and axial capacity of elements 3- seismic provisions	An automated procedure to design optimization of RC structures conformed to the ACI318-08 code and standard 2800-code recommendations

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Aydogdu & Saka (2012)	2012	ACO	-	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement 3- Constructability	1- Four case studies including two regular and two irregular space steel frames were analyzed using the proposed methodology as: 105-meber 2-bay 5-storey regular frame, 460-member 3-bay 20-storey irregular frame, 568-mebr 4-bay 10-storey regular frame, and 1860-member 20-storey irregular frame 2- Different combinations of dead, live, snow, and wind loads were applied to the structure 3- Two design procedures were considered including with and without warping loads
Gholizadeh & Fattahi (2012)	2012	MPSO	PSO, CSS, IACO, and TLBO	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement 3- Constructability	Two frame structures were optimized using the proposed methodology as (i) 3b-24s affected by horizontal loads (ii) 3D 20-storey braced steel space frame with 1040 elements affected by dead, live and wind loads
Kaveh & Talatahari (2012)	2012	CSS	HS, ACO, PSO, PSOPC, HPSACO, ICA, and IACO	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement	Three case studies were explored in this effort as follows: (i) 3b-15s frame affected by vertical and horizontal loads, (ii) 3b-24s frame affected by horizontal loads, and (iii) 290-member 10-storey space frame affected by gravity and wind forces

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Phan, Lim, Sha, Siew, et al. (2013)	2013	GA	-	Minimizing cost per unit length of building with mixed continuous and discrete design variables	1- Constraints were applied to columns as rafters as: axial compression and bending, distortional buckling, and combined bending and shear 2- Constraints for braces were compressive and tensile strengths	Four case studies were analyzed in this research as: (i)- unbraced portal frame with fixed topology, (ii)- unbraced portal frame with variable pitch, (iii)- braced portal frame with fixed pitch and fixed frame spacing, and (iv)- braced frame with variable pitch and variable frame spacing
Kazemzadeh Azad, Hasançebi, & Kazemzadeh Azad (2013)	2013	BB-BC, MBB-BC, and EBB-BC with and without UBS strategy	-	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement	1- Two following space frames were optimized using the proposed strategies: 135-member and 1026-meber steel frames 2- 10 combinations of dead, live and earthquake loads were applied to the structures
Talatahari, Khalili, & Alavizadeh (2013)	2013	PSO, APSO	GA, ACo, IACO, HBB-BC, and ICA	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement	1- Two numerical examples were resolved using the proposed algorithm as 1-bay 8-storey and 3-bay 15-storey 2- The first case was supposed to endure horizontal loads while the second one was affected by both vertical and horizontal loads

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Yang, Bletzinger, Zhang, & Zhou (2013)	2013	PMGCPSO	CMA-ES	Steel volume minimization	1- Elemental Stress 2- Displacement	1- Performance of the proposed algorithm was examined through two size optimization examples (2b-2s and 3b-3s frames) and one brace layout optimization (3b-3s frame). 2- All the frames were affected by nodal concentrated vertical and horizontal loads in addition to moment
Camp & Huq (2013)	2013	BB-BC	GA and SA	Cost and CO_2 minimization with discrete design variables	1- Elemental stress 2- Serviceability 3- Geometrical constraints	1- Three case studies were resolved as a 2b-4s and two 2b-6s frames 2- Applied loads were combined by dead, live, and wind loads
Gong, Xue, & Xu (2013)	2013	MOGA	-	A multi-objective approach based on: 1- Minimizing the cost 2- Minimizing seismic input energy to SFRS 3- Maximizing the hysteretic energy of fuse members	1- The plastic deformation on fuse members 2- The plastic deformation constraints on non-fuse members 3- Inter-story drift constraints.	1- An EBF braced frame from an office building in Vancouver, Canada was resolved 2- The applied loads to the model were seismic weight and accompanying gravity loads

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Kaveh & Zakian (2013)	2013	CSS and IHS	-	Weight minimization with discrete design variables	1- Lateral displacement in time history analysis 2- Elemental stress and relative displacement in dynamic-static analysis	1- Four numerical case studies were resolved to check the efficiency of proposed methods as: (i)- a 4-story planar steel shear frame, (ii)- a 4-story planar steel moment frame, (iii)- a 8-story planar steel shear frame, and (iv)- a 8-story planar steel moment frame 2- Two different analysis were established during the modeling: (i) time-history analysis, and (ii) dynamic-static analysis 3- Three earthquake time-history records were applied to the structure as: El Centro (N-S component, 1940), Kobe (090 component, 1995), and Tabas (LN component, 1978)
Hasancebi & Carbas (2014)	2014	BAT	HS, TS, BB-BC, MBB-BC, EBB-BC, and iSA	4- Weight minimization with discrete design variables	1- Elemental stress 2- Displacement 3- Geometrical constraints	Three case studies were resolved using the proposed algorithm as follows: 132-member unbraced steel frame affected by two combinations of gravity and earthquake loads, a 209-member industrial building affected by six combinations of dead, crane, and wind loads, and an 1860-member high-rise braced frame affected by dead, live, snow and wind loads

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Murren Khandelwal (2014)	2014	DDHS	GA, HS, ACO, IACO, and HPSACO	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement	Three case studies affected by vertical and horizontal loads were optimized using the proposed algorithm as: (i) 2b-3s, (ii) 3b-24s, and (iii) 3b-15s steel moment frame
Yassami& Ashtari (2014)	2014	FGA	GA	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement	1- Three case studies were resolved as a 3b-5s, 3b-9s and 3b-3s frames 2- Applied loads were combined by dead, live, and seismic loads
Yassami & Ashtari (2014)	2014	GA, FGA, and ABC	-	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement	1- Three case studies were resolved as a 3b-5s, 3b-9s and 3b-3s frames 2- Applied loads were combined by dead, live, and seismic loads
Kaveh & Nasrollahi (2014)	2014	CSS	GA and ACO	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement	1- Two case studies were resolved as a 4b-3s and 5b-9s 2- Applied loads were combined by dead, live, and seismic loads 3- Push-over analysis was considered in the design procedure 4- Four performance levels were applied to the design procedures as operational, immediate occupancy, life safety, and collapse prevention
Maheri & Narimani (2014)	2014	EHS	GA, ACO, HS, IACO, PSO, TLBO, and MMDGA	Weight minimization with discrete design variables	1- Elemental Stress 2- Displacement	1- Four case studies were resolved as a 2b-3s, 1b-10s, 3b-24s and a spatial 744-member steel frame. 2- 2D frames were affected by one combination of vertical and horizontal loads in addition to a 3D frame affected by two combinations dead, live, snow and wind loads.

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Saadat, Camp, & Pezeshk (2014)	2014	MOGA	-	Multi-objective optimization of two following objectives using discrete design variables: 1- the present value of the total economic cost (PC_t^T) 2- expected annual social loss (EASL)	1- Two hazard levels requirements including collapse prevention and immediate occupancy 2- Strong column-weak beam criteria	1- A FEMA-SAC structure was considered for numerical simulation 2- Inelastic time-history analysis was used in the design procedure
Kaveh, Bakhshpoori, & Azimi (2014)	2014	CS	-	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement 3- Geometrical constraints for beam-column connections	1- Three case studies were resolved using the proposed methodology including a 5-story 325-member regular moment frame and 8-story 504-member regular braced frame in addition to an irregular 9-story 499-member steel frame 2- All the cases were affected by dead and live loads 3- Two first cases were analyzed using equivalent static and spectral analysis and the third one was analyzed only based on spectral analysis
Alberdi & Khandelwal (2015)	2015	ACO, GA, HS, PSO, SA, TS, DDHS, AHS, and iSA	-	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement 3- Geometrical constraints for beam-column connections	In order to examine the robustness of utilized algorithms five case studies were resolved as three 2D frames (i.e., 3b-3s moment frame, 5b-14s moment frame, and 5b-14s braced frame) and two 3D frames (i.e., 5b-5b-20s moment frame and 5b-3b-25s braced frame)

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Gholizadeh & Poorhoseini (2015)	2015	MDEO	ACO, TS, ES, SA, HS, TLBO, HPSACO, ICA, CSS, and DEO	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement 3- Geometrical constraints for beam-column connections 4- Geometrical constraints for column size to prevent soft story	1- Model verification was conducted using two space frames as 105-member regular steel space frame and a 568-member unbraced steel space frame 2- The first case was affected by three combinations of dead, live, snow, and wind loads, and the second case was subjected to vertical and unfactored wind loads
Alberdi, Murren, & Khandelwal (2015)	2015	GA, HS, ACO, and TS	-	Cost minimization as result of cost of material and connections with discrete design variables	1- Elemental stress 2- Displacement 3- Geometrical constraints for beam-column connections	1- Model verification was conducted using two planar frames as 5b-5s and 5b-10s frames 2- Both cases were affected by three combinations of dead, live, roof, and wind loads 3- The first case was analyzed based on considering fixed and variable connections topology along with regarding and disregarding constructability constraints
Kazemzadeh Azad & Hasancebi (2015)	2015	GSS	UBB-BC, UMBB-BC, UEBB-BC, and UPSO	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement	1- Model evaluation was conducted using a planar 3b-15s steel frame in addition to three 3D frames as 135-member space frame, 3860-member, and 11,540-member steel frames 2- The first case was affected by vertical and horizontal loads and 3D frames were design for 10 combinations of dead, live and wind loads
Gharehbaghi & Khatibinia (2015)	2015	PSO	-	Cost minimization	1- steel ratio 2- flexural and axial capacity of elements 3- seismic provisions	The proposed IRM consists of three components: SA, K-means clustering approach, and WWLS-SVM.

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Hadidi & Rafiee (2015)	2015	HS-BB-BC	HS, BB-BC, and HS-PSO	Total cost minimization with discrete design variables	1- Elemental stress 2- Displacement 3- Geometrical constraints for beam-column connections	1- Three case studies were examined through the proposed approach as (i) 1b-9s frame, (ii) 4b-10s, and (iii) 4b-24s 2- All the frames were imposed by vertical and horizontal loads Nonlinear analysis was considered based on non-linear moment-rotation behavior of connections and P-Δ effects
Talatahari, Gandomi, Yang, & Deb (2015)	2015	ES-DE	GA, HS, ACO, DE, OC, ICA, IACO, HPSACO, and HBB-BC	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement	1- Four moment resistant frames were considered as (i) 1b-8s, (ii) 3b-15s, (iii) 3b-24s, and (iv) 290-member 10-story space frame 2- The first and third cases were subjected to the lateral loads and the second and fourth endured both lateral and vertical loads
Carbas (2016)	2016	EFA	PSO, CS, and FA	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement 3- Geometrical constraints for beam-column connections	1- Model evaluation was done through two numerical examples as a 105-member regular space frame and a 568-member unbraced steel space frame 2- The first example was supposed to endure three different combinations of dead, live, snow and wind loads, and the second case was affected by vertical loads in addition to unfactored wind load

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Carbas (2016)	2016	BBO	TLBO, ABC, DHS, ACO, and adaptive FA	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement 3- Geometrical constraints for beam-column connections	1- Two real-world space frames were solved using the proposed algorithm as a 4-story 428-member and 8-story 1024-member 2- Those cases were affected by four combinations of dead, live, snow, and wind loads
Gholizadeh & Poorhoseini (2016)	2016	IDEO	GA and DEO	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement 3- Geometrical constraints for beam-column and column-column connections	Two types of numerical case studies were solved in this study as follows: 1- a 3b-24s planar frame solved using linear analysis and not considering geometrical constraints, and 2- three 5-bay 6-, 9-, and 12-story braced frames with fixed and optimized brace layout
Aydoğdu, Akın, & Saka (2016)	2016	LFABC	ABC, ACO, and DHS	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement 3- Geometrical constraints for beam-column and column-column connections	1- Three case studies were solved as follows: 4-story 132-member, 4-story 428-member, and 8-story 1024-member steel space frames 2- The first case was affected by seven combinations of dead, live, snow, earthquake and wind loads, and two others were affected by four combinations of dead, live, snow, and wind
Kaveh & BolandGerami (2016)	2016	Cascade ECBO	ECBO	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement 3- Geometrical constraints for beam-column connections	1- Three case studies were solved using the proposed cascade optimization as 1860-, 3590-, and 3328-member steel space frame 2- All the cases were affected by dead, live, snow, and wind loads

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Papavasileiou & Charmpis (2016)	2016	ES	-	Cost and brace topology optimization	1- Elemental stress 2- Displacement 3- Maximum fundamental period of structure	Three different space composite frames were resolved using the proposed methodology as follows: (i) 6-story 5×5-bay, (ii) 6-story 8×8-bay, and (iii) 4-story 5×5-bay composite buildings.
Carraro, Lopez, & Miguel (2016)	2016	SGAO	-	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement	1- Three case studies were examined using the proposed algorithm as follows: (i) 2b-3s frame, (ii) 1b-10s frame, and (iii) 3b-24s frame 2- All the frames were affected by vertical and horizontal loads
Daloglu, Artar, Özgan, & Karakas (2016)	2016	GA and HS	HS, ACO, and TS	Weight minimization considering soil-structure interactions with discrete design variables	1- Elemental stress 2- Displacement 3- Geometrical constraints for beam-column and column-column connections	1- Three case studies were examined using the proposed algorithm as follows: (i) 2-story 21-member irregular space frame, (ii) 4-story 84-member space frame, and (iii) 20-story 460-member irregular space frame 2- All the frames were affected by vertical and horizontal loads
Prendes-Gero, Álvarez-Fernández, López-Gayarre et al. (2016)	2016	GAET	-	Total cost minimization with discrete design variables	1- Elemental stress 2- Displacement	1- Three case studies were examined using the proposed algorithm as follows: (i) 1b-2s frame, (ii) 2b-4s, and (iii) 4b-4s frame 2- All the frames were affected by distributed and point horizontal and vertical loads

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Gholizadeh, Davoudi, & Fattahi (2017)	2017	MFO and EMFO	GA, HS, ACO, DE, ES, ES-DE, IACO, TLBO, and MSPO	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement 3- Geometrical constraints for beam-column and column-column connections	1- Three numerical cases were examined as follows: (i) 1b-10s moment frame, (ii) 3b-24s moment frame, and (iii) 20-story braced frame 2- Two first frames were affected by external vertical and horizontal loads, and the third case was affected by dead, live and wind loads
Kaveh, Ghafari, & Gholipour (2017)	2017	PSO and ECBO	-	Cost minimization as result of cost of material and connections with discrete design variables	1- Elemental stress 2- Displacement 3- Geometrical constraints for beam-column and column-column connections	1- Three different moment frames were designed to evaluate the proposed algorithms' efficiencies as follows: (i) 3b-15s, (ii) 5b-5s, and (iii) 5b-10s special frame 2- All the cases were affected by dead, live and earthquake loads
Gholizadeh & Baghchevan (2017)	2017	CMOFA	MOFA	Multi-objective optimization of two following objectives using discrete design variables: 1- weight minimization, 2- inter-story drift maximization	1- Elemental stress 2- Displacement 3- Geometrical constraints for beam-column and column-column connections	1- Three different moment frames were designed to evaluate the proposed algorithms' efficiencies as follows: (i) 2b-3s, (ii) 3-bay 6-story, and (iii) 4-bay 12-story 2- All the cases were affected by dead, live and earthquake loads based on three performance levels (i.e., immediate occupancy, life safety, and collapse prevention)
Maheri, Shokrian, & Narimani (2017)	2017	HBMO and EHBMO	GA, ACO, PSO, TS, Adaptive HS, IACO, HS, TLBO, ICA, MMDGA, and EHS	Weight minimization with discrete design variables	1- Elemental stress in the 1st case 2- Elemental stress and displacement in the 2nd and 3rd cases 3- Elemental stress, displacement, and geometrical requirements for the connections in the 4th case	Four cases resolved as follows: (i) 2-bay 3-story, (ii) 1-bay 10-story, (iii) 3-bay 24-story, and (iv) 744-member space frame

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Kaveh, Ghafari, & Gholipour (2017)	2017	SA, PSO, ABC, WOA, GWO, HS, CBO, ECBO, and IWO	-	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement 3- Geometrical constraints for beam-column and column-column connections	1- Three examples were solved using the proposed methodology as follows: (i) regular 6-story frame, (ii) irregular 12-story frame, and (iii) a regular 10-story frame 2- Dead, live and earthquake loads were applied to the models 3- Three types of moment frames were considered for every single case as OMF, IMF, and SMF 4- Soil class was considered to be "*C*" and seismic load was evaluated using IBC2006 with damping ration of 0.05
Gholizadeh & Ebadijalal (2008)	2018	CMO	ES, SA, MDEA, and IDEO	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement 3- Geometrical constraints for beam-column and column-column connections	Four case studies were tackled using the proposed approach as follows: 3-bay 24-story as well as 5-bay 3-, 5-, and 10-story braced steel frames
Gholizadeh & Milany (2018)	2018	FWA and IFWA	ES, SA, MDEA, DE, DEO and ES-DE	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement	1- In this study two case studies were solved as braced and unbraced 3-bay 24-story frames 2- Unbraced frame was affected lateral and vertical loads and the braced frame was considered to endure dead, live, snow and wind loads
Farshchin, Maniat, Camp, & Pezeshk (2018)	2018	SBO	GA, HS, ACO, SGAO, TLBO, ESDE, and EWOA	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement	1- Three case studies were solved using the proposed algorithm including two-bay three-story, one-bay ten-story, and three-bay twenty four-story moment frames 2- Vertical and horizontal loads were exposed to the tackled frame structures

Table 2. (Continued).

References	Year	Utilized Algorithms	Compared Algorithms	Objective	Constraints	Model development
Artar & Daloglu (2018)	2018	GA and HS	ES, ACO, and TS	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement	Two different steel frames affected by gravity and wind loads were solved as follows: two-story sixteen-member steel space frame, and ten-story 568-member steel space frame.
Bybordiani & Kazemzadeh Azad (2019)	2019	BB-BC	-	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement	The proposed methodology was applied to 8-bay 5-story and 8-bay 10-story braced frames
Zakian (2019)	2019	PSO, CSS, TLBO, GWO, and IGWO	-	Weight minimization with discrete and continuous design variables	Natural frequency	Six following case studies were optimized using the proposed algorithms: (i) 1-bay 2—story planar moment frame, (ii) 1-bay 7-story planar moment frame, (iii) 3-bay 10-story planar moment frame, (iv) 1-story 8-member space frame, (v) 10-story 180-member space frame with continuous and discrete design variables, and (vi) 41-story space frame with continuous and discrete design variables.
Hassanzadeh & Gholizadeh (2019)	2019	CMO	-	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement	In this study three cases were solved as follows: 5-, 10-, and 15-story SCBFs
Kaveh, Biabani Hamedani, Hosseini, Bakhshpoori (2020)	2020	ABC, BB-BC, CPA, CS, TEO, WEOA, and TLBO	-	Weight minimization with discrete design variables	1- Elemental stress 2- Displacement	Three case studies were analyzed using the proposed algorithms as follows: (i) 1-bay 10-story, (ii) 3-bay 15-story, and (iii) 3-bay 24-story moment frames

4.3. dam optimization

Dams are among the most strategic structures for every country due to their economic and political role. Hence, any issue in their performance will end up catstrophic disasters due to the level of money and life loss. On the other hand, bulk materials of these monsters make the final cost considerable. Therefore, any effort in decreasing the final cost while preserving the serviceability and safety at high level would be highly worthwhile. Those facts have made the optimum design of dams a hot debate in civil engineering. A detailed review of this sort of studies is presented in this section.

Seyedpoor, Salajegheh, Salajegheh, & Gholizadeh (2009) explored the efficiency of a combination of particle swarm optimization, FIS, and neural network for shape optimization of under earthquake loading. In this way, two strategies were adopted to improve the optimization process. First, they tried to anticipate the structural response of fewer dam design variables applying an adaptive neuro-fuzzy inference system. Second, the arch-dam response was predicted by an adequately trained wavelet radial basis function neural network employing. Seyedpoor, Salajegheh, Salajegheh, & Gholizadeh (2011) also examined a hybrid version of particle swarm optimization (PSO) with simultaneous perturbation stochastic approximation (SPSA) algorithm for shape optimization of arch dams subjected to earthquake loading. They compared the combination of SPSA–PSO those result of SPSA and PSO. Results showed that the SPSA–PSO converges to a superior solution compared to the SPSA and PSO.

Khatibinia & Khosravi (2013) tackled shape optimization of concrete gravity dams, including dam–water–foundation rock interaction subjected to earthquake loading. They used a hybrid approach combination of improved gravitational search algorithm (IGSA) with orthogonal crossover(OC). They optimized four benchmark problems using IGSA-OC and compared the results with the standard gravitational search algorithm (GSA)and the other modified GSA methods. Results showed that the proposed IGSA-OC outperformed the standard GSA, IGSA, and PSO in weight minimization and convergence. Khatibinia, Chiti, Akbarpour, & Naseri (2015) also explored the shape optimization of concrete gravity dams effects subjected to earthquake loading. The optimization was conducted using the integration of an improved gravitational search algorithm (IGSA) and the orthogonal crossover (OC). In this study, the dam body was treated as a two-dimensional structure involving the geometry and material nonlinearity effects using the Drucker–Prager model, and weighted least squares support vector machine (WLS–SMV) regression model was utilized to approximate the nonlinear dynamic analysis.

Kaveh & Mahdavi (2013) examined the efficiency of three optimization algorithms (PSO, CSS, and CSS-PSO) for shape optimization of double-curvature arch dams under earthquake loading. In this way, the geometrical model of the tackled arc dam was formed by two different features: 1- the shape of the central vertical section and 2- the horizontal section's shape—both the curvature and the thickness change horizontal and vertical directions. The minimum cost or concrete volume design of the dam was the main objective of this study, considering the constraints defined by stress capacity and geometrical conditions. Model evaluation was conducted through two case studies as (i) concrete volume minimization of Morrow Point arch dam and (ii) cost minimization of a hypothetical well-known benchmark arc dam. A parametric study was also established based on changing the depth of water and earthquake intensity.

Mahani, Shojaee, Salajegheh, & Khatibinia (2014) explored the double arch concrete dams optimization under earthquake loading. They integrated ant colony optimization(ACOR) and particle swarm optimization (PSO) in the optimization process. In this way, a preliminary optimization is accomplished using ACOR then PSO was applied using the optimal initial swarm of the ACOR. The numerical results showed that ACOR–PSO converges to better solutions and provides a faster convergence rate compared to the application of ACOR and PSO individually.

Mirzaei, Akbarpour, Khatibinia, & Siuki (2015) tackled the shape optimization of homogeneous earth dams using particle swarm optimization (PSO) incorporated to weighted least squares support vector machine (WLS-SVM). The objective function was minimizing the seepage through the dam body and a homogeneous earth dam's weight. The design variables were considered the upstream and downstream slopes of the earth dam, the length of oblique and horizontal drains, and the drains' angle. The results showed that the seepage through the dam body as an objective function is more important than the earth dam's weight. Chiti, Khatibinia, Akbarpour, & Naseri (2016) also examined the shape optimization of concrete gravity dams subjected to earthquake load using a reliability-based design optimization (RBDO). In this way, subset simulation was integrated with a hybrid optimization method to solve the RBDO approach of concrete gravity dam. In this study, the concrete gravity dam was treated as a two–dimensional structure involving the material nonlinearity effects and dam–reservoir–foundation interaction.

4.4. Miscellaneous

In light of an optimization algorithm's robustness to solve difficult problems, a wide range of efforts have been conducted to find their civil engineering applications. In the following, the efficiency of those algorithms to deal with structural engineering problems is examined and discussed in detail. The initial efforts in handling civil engineering problems using heuristic approaches can be found in different studies accordingly. Changwen (1989) and Simões (2001) utilized the same approaches based on fuzzy optimization following two phases to handle structural engineering problems. Changwen (1989) applied this method to a three-bar truss and corrugated bulkhead. Simões (2001) considered solving a prismatic beam, portal frame, and reinforced concrete slab. Jenkins (1991) applied a GA to minimize the total mass of different structures. In this study, the optimum design of a trussed-beam roof, 2D truss structures, and thin-walled cross-section.

Grierson & Pak (1993) employed a GA for size, shape, and topology optimization of steel frameworks. Riche & Haftka (1993) tackled the optimization of laminate stacking sequence for buckling load maximization using a GA. Xie & Steven (1994) proposed an evolutionary approach to find optimal shape and topology of structures (i.e., L-shape plate and short beam) based on the natural frequency maximization or minimization. Liu, Haftka, & Akgun, (n.d.) utilized a GA to optimize composite wing structures. To this end, a two-level optimization approach was proposed with the following features: 1- wing-level optimization dealing with weight minimization of the wing, and 2- panel-level optimization dealing with buckling load maximization based on a given amount of piles in each direction. Botello, Marroquin, Oñate, & Horebeek (1999) employed GA, SA, and a combined approach based on GA and SA algorithms (GSSA) for optimum design of some structural benchmark problems (i.e., planar bar structure, 10-bar truss structure, pedestrian bridge structure, electric tower, and a tridimensional structure with 2440 elements).

In 2000, Liu, Haftka, & Akgün (2000) developed a two-level structural optimization procedure for designing a composite wing. To this end, several constraints were applied based on strength and buckling constraints. The optimization procedure was conducted based on two main phases, including wing-level design and panel-level design. In the prior phase, the main objective was the minimization of the total weight of the structure as a function of thicknesses of upper and lower skin panels. In the latter phase, the main effort was finding the optimal stacking sequence for a given amount of piles that maximizes the buckling load factor. The GA was responsible for automating the design procedure. The proposed model was validated through six-variable, eighteen-variable, and fifty-four-variable design problems.

In 2002, Hansel, Treptow, Becker, & Freisleben (2002) developed two different topology optimization approaches to find the minimum weight of laminate structures. Those two approached were based on a heuristic optimization algorithm and a GA-based topology optimization. The heuristic approach considered numbers of laminate elements composed of four single layer elements and equal thicknesses. Numbers of strength constraints were applied to the design procedure to guarantee enough load-carrying capacity. In the GA-based approach, the material distribution and the local reinforcement directions were adapted to reach the optimum weight of structures. Both approaches were examined through a cantilever plate and an L-shaped cantilever.

In 2004, Burczyński, Kuś, Długosz, & Orantek (2004) studied shape and topology optimization as well as defect identification using distributed evolutionary algorithms. In this way, the design variables were defined as shape, topology, and material parameters. The proposed evolutionary scheme was based on the coupling finite element method and the boundary element method to find the optimal design. Four different case studies were presented to examine the efficiency of the proposed model as follows: 1- identification of hole in an elastoplastic 3D structure, 2- evolutionary shape design of a thermomechanical structure, 3- identification of voids for a thermomechanical problem, and 4- dynamically loaded plate. In 2005, Wang & Tai (2005) selected a GA for topology optimization of structures using a bit-array representation method. In this study, the main effort was addressing the design connectivity issue by defining an equality constraint. The optimization process was a single objective function defined in two different ways as follows: 1- minimizing compliance with a constraint on the volume fraction, and 2- minimizing the weight with a constraint on the maximum displacement. Several case studies were explored using the proposed methodologies to examine their efficiencies in terms of finding the topologies with higher structural performance, less unusable material, and fewer separate objects in the design domain.

In 2006, Bochenek & Foryś (2006) developed an improved PSO algorithm for structural optimization considering post-buckling behavior. Those modifications accounted for both the velocity updating and constraint handling. In this way, an additional term was embedded into the formula to represent the distance between the particle position and the position of the best particle among its neighbors. For inequality constraint handling, a method called "controlled reflection" was proposed where the violated particle will move on the boundary or reflected back to the feasible solution area. The objective function was defined as the sum of squared distances between the given equilibrium path and the reconstructed one. This modified algorithm was applied to several structural simple rigid–elastic, finite-degree-of-freedom models that catch the post-buckling behavior as follows: 1- a model of the column, 2- a model of the frame, 3- Koiter frame with additional support.

In 2008, Liu, Yi, Li, & Shen (2008) explored the application of a GA to structural topology optimization. In this study, the optimality of the structures was defined as finding minimum weight or strain energy. The applied constraints for minimum weight design and minimum strain energy were based on prescribed maximum displacement and prescribed total weight, respectively. Three case studies were resolved using the proposed methodology with different settings for prescribed total weight and displacement. Kaveh, Hassani, Shojaee, & Tavakkoli (2008) tackled structural topology optimization using an ACO algorithm. The main objective of this study was to minimize the strain energy to reach the stiffest possible structure. Four case studies were explored using the proposed methodology (i.e., simple beam, cantilever beam, knee structure, and a 3D bridge). The obtained results by ACO-based procedure was compared to a topology optimization research code called TOPS (Topology Optimization of Structures).

In 2009, Barakat & Altoubat (2009) studied the cost optimization of conical reinforced concrete water tanks. To that end, three evolutionary techniques were selected, including a shuffled complex evolution (SCE), a SA, and a GA. In order to describe the problem geometrically, a global cylindrical coordinate system was proposed. Thanks to axisymmetric shape, the problem was described independently of the rotational angle. The analyzing process was handled using the finite element method. Six design variables including the thickness of the wall at the base and the top of the tank, the thickness of the base, the depth of the tank, the angle made by the inner wall surface with the axis of symmetry, and the concrete compressive strength were proposed for describing the model. The utilized constraints for model qualification were applied to the design procedure was based on ACI requirements. Two methods of design, namely, working-stress design and ultimate strength design, were utilized. Numerical simulations were conducted to examine the effects of different optimization methods, the design methods, reinforcing bar size, water tank wall inclination, and material unit cost. The superiority of the SCE algorithm was indicated through several numerical case studies.

Luh & Lin (2009) utilized an ACO algorithm for structural topology optimization. To this end, a given continuum structure was discretized into several small square elements. For each element, two choices of either presence or absence were available for the material. The objective function was defined as the stiffness-to-weight ratio, where stiffness was inverse of topology's maximum displacement. The constraints were defined based on allowable stress. A cantilever plate was designed using the proposed methodology under four different loading cases where a downward point load was affected by different locations of the plate. In 2011, Luh, Lin, & Lin (2011) applied a binary PSO (BPSO) algorithm to the same problem and using the same strategy as Luh & Lin (2009). The obtained results were compared to the one recorded by ACO that indicated the better performance of BPSO in dealing with ACO.

In 2012, Muc & Muc-Wierzgoń (2012) utilized the ES algorithm for topology optimization of multi-layered idealized thin cylindrical shell structures. It was assumed that every given structure was constituted by stacking sequences of the individual layers in the laminate with prescribed fiber orientation. Therefore, in addition to the mentioned features for describing a trial structure's model, a finite number of key points on a curve for characterizing the external boundary of the structure were defined as the design variables. Two numerical examples were discussed in this study to assess the efficiency of the proposed method as follows: 1- stacking sequence optimization subjected to buckling and the First-Ply-Failure constraints, and 2- optimization of laminate configuration and shell thickness.

Kaveh & Ahangaran (2012) explored the discrete optimization of composite floor systems using social harmony search (SHS) algorithms. The objective function was defined as the total cost of the floor based on the costs of concrete, steel I beam, and shear studs. Six design variables were proposed to describe the trial models, namely, concrete compressive strength, concrete slab thickness, steel section shape, steel beam spacing, shear stud diameter, and the number of shear studs for one beam. The analyzing procedure was based on AISC-LRFD specifications and plastic design concepts. In this way, several constraints were applied to the design procedure based on flexural strength constraints, deflection constraints, shear, and spacing constraints. Numerical simulations were conducted for one span floor constructed with and without shores. The obtained results using the proposed algorithm states its more efficiency compared with ACO, HS, IHS, and highly reliable harmony search (HRHS) algorithms.

In 2013, Kociecki & Adeli (2013) explored the weight minimization of free-form steel space-frame roof structures using a two-phase GA. In this study, a discrete optimization was conducted using hollow structural sections (HSS). The design procedure was based on the AISC-LRFD code and ASCE-10 for dead, snow, wind, and seismic loading. The main objective was weight minimization of the structure as a function of the wall thickness of members in the roof, the wall thickness of members in the column group, width, height, and thickness of the roof and column members. Two free-form steel space-frame roof structures were resolved using the proposed methodology: (i) 224 ft (68.27 m) long, 75 ft (22.86 m) wide, and 27 ft (8.23 m) tall, with 278 structural members in the roof plus ten inclined columns, and (ii) 203 ft (61.874 m) long, 67 ft (20.422 m) wide, and 55 ft (16.764 m) tall, with 306 roof members and 34 inclined columns.

Kamyab Moghadas, Garakani, & Kalantarzadeh (2013) employed a FA for minimum weight design of double-layer scallop domes for static loading considering linear and non-linear behaviors. Nonlinear optimization dealt with geometrical nonlinearity effects. The analysis of every trial structure was conducted using ANSYS (2006) commercial software. AISC-ASD was selected to define the constraints based on the displacement of the joints and the stress of the members' limitations. Three case studies were presented and solved using the proposed procedure as three double-layer scallop domes with 6, 8, and 10 segments. The results indicated that the final design of the nonlinear structure was significantly less than that of the linear one. Nonlinear analysis reached to the final solution in a smaller number of generations than that linear. Increasing number of segments was resulted in decreasing the weight of linear and nonlinear structures.

Finotto, da Silva, Valášek, & Štemberk (2013) optimized topology and size of cabled-truss structures using a hybrid fuzzy-genetic system. The cross-sectional areas of the members and pre-stress levels in the cables were considered as the design variables to deal with sizing optimization. Topology optimization was concern about the distribution of the elements. The applied constraints to the design procedure were related to allowable stress and displacement. A nonlinear finite element approach was considered for structural analysis. 10-element and 15-element ground structures were resolved using the proposed methodology. The obtained results were compared to the truss structures with the same topology and bar elements. Cabled-trusses were found to be a significantly improved alternative for bar-trusses in terms of minimal weights. Amini & Ghaderi (2013) developed a hybrid optimization algorithm for optimal locating the structural dampers. Three different structures were tackled using the proposed methodology. The first case was a shear building with 16 stories subjected to El-Centro ground acceleration. The main objective was finding the best configuration of Magneto-Rheological (MR) dampers within six floors of a 16-story defined as minimizing the maximum shear base over the period of ground acceleration. In the second case, the optimal layout of eight viscous dampers was found for a two-dimensional truss structure. The objective function was defined as the minimization of the maximum infinity-norm of the displacement vector at the time t. A planar 3-span 10-story braced frame was selected as the third case study. In this case, the objective function was defined as minimizing the maximum shear forces in the columns of the ground floor over the period of ground acceleration.

In 2014, Sharafi, Hadi, & Teh (2014) considered an ACO algorithm for topology and layout optimization of reinforced concrete beams for dynamic responses. In this way, the final cost was determined based on the costs of concrete, longitudinal steel, shear steel, and formwork. Flexure, shear, and displacement of a multi-span continuous beam constituted by assembling numbers of uniform Euler-Bernoulli beam segments were evaluated based on its dynamic response to a time-dependent external force. The proposed concept was applied to a beam under two loading cases as 1- static uniformly distributed load (UDL), and 2- a moving point load along the beam. Bertagnoli, Giordano, & Mancini (2014) studied reinforcements' directions optimization in concrete shells using a GA. The finite element analysis was considered during the design procedure. In this way, a reinforced concrete shell was described by a sandwich element with two external layers and one internal layer. The objective function of this study was the minimization of steel reinforcement volume. The obtained results proved the effectiveness of the proposed method in handling the tackled problem.

Sadollah, Eskandar, & Kim (2014) utilized an MBA algorithm for geometry optimization of a cylindrical fin heat sink. To that end, the minimization of three different responses of electromagnetic emitted radiations, thermal resistance, and mass of the heat sink was defined as the main objectives. The design variables were the width of the heat sink, number of fins, fin height, and fin diameter. In addition to handling every objective independently, an additional objective function was defined as an error function as a weighted combination of the three aforementioned objectives. A benchmark problem was selected for numerical simulations and compared to the previous efforts (i.e., GA, Taguchi-based gray relational analysis, epsilon constraint method, Taguchi-based epsilon constraint method). The superiority of the MBA was proved based on its more optimal results. A parameter sensitivity analysis was also conducted to determine the effect of each variable on the objective values, while all the other parameters were kept fixed.

Gholizadeh & Shahrezaei (2015) utilized the BA algorithm for optimal placement of steel plate shear walls. Flexural and axial forces in the beams and columns as well as tension in the web plate were calculated using the finite element method through ANSYS software. The orthotropic membrane model proposed in AISC was used to distribute the forces between the wall members. Two different frame structures were subject to size optimization as a three-bay, five-story, and a three-bay, 10-story steel frame. Those structures were subjected to a uniform distributed gravity load and earthquake concentrated loads. The optimization procedure was conducted based on fixed shear walls layouts and compared with an optimized configuration of the walls. The total weight of the structure was minimized subject to strength and displacement constraints defined based upon AIS-LRFD specifications. The proposed methodology for optimizing the layout of shear walls resulted in a considerable decrease in final designs rather than a fixed layout. Furthermore, a comparison of the results with GA and PSO demonstrated the superiority of BA in handling the tackled problem.

In 2016, Kaveh, Talaei, & Nasrollahi (2016) tackled the problem of large-span prestressed concrete slabs optimization using a probabilistic PSO (PPSO) algorithm. A probabilistic approach was incorporated into the velocity updating rules of the original PSO. The objective function was defined as the final cost as a result of the cost of concrete and tendon. Every trial model was developed using the following design variables: the thickness of the slab, number of tendons in X-direction, number of tendons in Y-direction, the diameter of tendons in the X-direction, the diameter of tendons in Y-direction, tendon eccentricity at one end of the slab, tendon eccentricity at the other end of the slab, tendon eccentricity at the middle of the slab, the allowable tensile stress of tendons. The effective constraints to reach a valid design are defined based on Canadian standard association (CSA) requirements, including stress in concrete, the stress in tendons, ultimate bending moment, minimum factored resistance, punching shear, and maximum/minimum eccentricity. SAP2000 was utilized to handle the analyzing procedure. The efficiency of PPSO was examined by considering a prestressed concrete slab and compared to the PSO and HS algorithms. Moreover, a sensitivity analysis was conducted on two probability terms in the PPSO algorithm to find their best configurations.

Kaveh, Maniat, & Arab Naeini (2016) tackled the cost optimization of post-tensioned concrete bridges using an MCBO algorithm. The objective function was defined as the final cost minimization of the bridge superstructure as a result of material and construction costs of concrete, prestressing steel, reinforcement, and formwork. Seventeen following design variables were defined to describe the model: concrete strength, girder depth, top slab thickness, bottom slab thickness, web thickness, length of cantilever, end thickness of cantilever, initial thickness of cantilever, length of haunch, width of haunch, number of strands per tendon, number of tendons in each web, number of anchorages in each row, lowest anchorage position, prestressing force, top slab reinforcement ratio, and cantilever slab reinforcement ratio. The applied constraints to the design procedure were determined in accordance with AASHTO (2002) standard regulations as follows: 1- flexural working stress, 2- allowable stress in prestressing steel, 3- ultimate flexural strength, 4- ductility, 5- ultimate shear strength, 6- deflection, 7- slabs design, and 8- cantilever slab deflection. A typical prestressed box girder bridge was resolved using the proposed methodology and compared with the results of PSO and CBO. The effect of different parameters on the final cost variations was examined through a sensitivity analysis.

In 2017, Toklu, Bekdaş, & Temur (2017) utilized an HS algorithm for analyzing cable structures through energy minimization. In this way, a structural system was found to be in an equilibrium state only if the total potential energy is minimum. Total potential energy was defined as a function of nodal displacements in all three dimensions for every free node. Six numerical cases were analyzed using the proposed methodology as follows: 1- Flat cable net 1×1, 2- Flat cable net 2×1, 3- Flat cable net 2×2, 4- Hyperbolic paraboloid net, 5- Spatial cable network, and 6- Dual cable. The proposed optimization algorithm outperformed other previous methods. Pedro, Demarche, Miguel, & Lopez (2017) developed a two-stage optimization approach for the optimum design of steel-concrete composite I-girder bridges. In the first step, a simplified structural model developed by a designer was selected as the starting point for global optimization. The utilized algorithm at this stage was BSA, FA, GA, ICA, and SGA. The second step was devoted to refining the solution from the first step through a local search using an SGA combined with a finite element method to reach the global optimal solution. In this study the main objective was total cost of bridge as a function of four groups of design variables: 1- Geometric values, 2- Material characteristics, 3- Reinforcement, and 4- The number of the beams used in the bridge. Structural constraints were defined based on the AASHTOO (2002) standard recommendations for reinforcement, shear stress, and maximum deflection in the slab, allowable stress and maximum deflection in the girders, and shear connector, support stiffener, transversal stiffener, longitudinal stiffener, and diaphragm of accessories. Based on the results, it was stated that the structural cost was decreased by 7.43% in the first step and up to 9.17% at the end of the optimization procedure.

Talaei, Nasrollahi, & Ghayekhloo (2017) utilized a hybrid PSO and HS algorithm, so-called PSOHS, for optimum cost design of prestressed concrete slabs. The objective function was defined as the final cost of structure as a result of concrete and tendons costs. The design variables for describing a trial model were the slab’s thickness, the number of tendons in the x-direction, the number of tendons in the y-direction, the diameter of tendons in the x-direction, the diameter of tendons in the y-direction, the tendon eccentricity at one end of the slab, the tendon eccentricity at the other end of the slab, the tendon eccentricity at the middle of the slab, and the allowable tensile stress of tendons. Canadian standard association requirements were considered to form the following applied constraints to the design procedure: 1- stress in concrete, 2- stress in concrete, 3- stress in tendons, 4- ultimate bending moment, 5- minimum factored resistance, 6- punching shear, and 7- maximum/minimum eccentricity. The SAP2000 software was utilized to analyze the structures. The proposed modified algorithm was compared to the original PSO by solving a large-scale slab. The results indicated that the PSOHS was better than the original PSO due to slightly better solutions and being less sensitive to the hyperparameters setting.

Kaveh & Ghazaan (2018) tackled the weight optimization of large-scale dome structures subject to natural frequency constraints using a hybrid meta-heuristic algorithm. This hybrid approach, named MDVC-UVPS method, combined the vibrating particles system (VPS), multi-design variable configuration (Multi-DVC) cascade optimization, and an upper bound strategy (UBS). Four numerical case studies were selected to evaluate the effectiveness of the proposed algorithm as follows: 120-bar dome truss, 600-bar single layer dome truss, 1180-bar dome truss, and 1410-bar double-layer dome truss. The final results were compared with DPSO, ECBO, ECBO with cascade optimization, and VPS. The results revealed that MDVC-UVPS outperformed other mentioned algorithms in handling this tackled problem.

In 2018, Kaveh & Mahjoubi (2018) employed a lion pride optimization algorithm (LPOA) to handle the optimum weight design of double-layer barrel vaults. The design procedure was formed based on AISC-ASD regulations for stress, slenderness, and displacement. The efficiency of the LPOA was examined through a comparison with PSO, CS, and ABC algorithms in handling three large-scale benchmark optimization problems. Moreover, the final results were compared with previous findings using a wide variety of methods, such as GA, ACO, HS, BB-BC, MBB-BC, MCSS, IMCSS, ADS, CBO, and ECBO algorithms as well as engineering designs. Seo, Kim, & Kwon (2018) utilized an ACO algorithm to find the optimal number and locations of seismically retrofitted RC columns for a school building. Nonlinear time history analysis coupled with finite element method was conducted using LS-DYNA commercial software for seismic structural analysis. Glass fiber-reinforced polymer (GFRP) was utilized for retrofitting the columns. The objective function was defined in a way that minimized the total number of retrofitted columns as a function of retrofitted columns distribution. The design procedure was governed by several constraints for allowable strains of retrofitted and non-retrofitted column members and inter-story displacement. Model evaluation was triggered for a three-story RC structure consisting of 62 columns on each floor, which was designed originally for non-seismic loading. The optimization procedure proposed retrofitting 60.2% of the columns would help to endure peak ground acceleration of 0.2g.

Kaveh & Rezaei (2018) considered the problem of shape and size optimization of domes using the ECBO algorithm. In this way, geometrically nonlinear analysis of large-scale double-layer domes and suspend-domes with rigid and pinned connections were conducted during the volume minimization procedure. The design variables for describing the tackled problems were the length of the strut, the cable initial strain, the cross-sectional areas of the cables and steel elements, and the height of domes. Stress, the slenderness of the elements, and nodal displacements were the applied constraint to the optimization procedure based on AISC-LRFD. Two numerical case studies were explored as follows: 1- Lamella suspend-dome with pin-jointed and rigid-jointed connections, and 2- double-layer Lamella domes.

In 2019, Kaveh & Ghafari (2019) applied nine optimization algorithms to size and shape optimization of steel pitched roof frames with tapered fabricated members. In this study, the total weight of the structure was related to seven design variables that determined flange width and thickness as well as web height and thickness at three sections of the frame. Beams and columns were tapered I-shaped members fabricated by steel plates. A finite element method that considered P-Δ effects was selected to handle the analyzing procedure using SAP2000 software. Nine following metaheuristic algorithms were examined through two numerical case studies, including CBO, GWO, HS, ABC, ECBO, IWO, PSO, SAO, and WOA. Seven load combinations were applied to the structures resulted from dead, live, earthquake, wind, snow, and roof live loads. Strength design criteria and allowable vertical and horizontal displacements were assigned to the constraints, according to AISC360-10 (2010) and AISC341-10 (2010). A sensitivity analysis was also conducted over the variation of different roof angles, height, and tapered length ratios.

Kaveh & Javadi (2019) explored the efficiency of chaos-based FA for minimum weight design of large-scale braced steel domes subject to natural frequency constraints. Two chaotic maps (Logistic and Gaussian maps) were substituted for attractiveness and light absorption coefficients to improve the FA's performance by decreasing its randomness. Three numerical simulations were solved using those proposed algorithms as follows: (i) fifty-two-bar dome truss, (ii) 600-bar single-layer dome, and (iii) 1410-bar double layer dome truss. Those two chaotic FAs (CLFA and CGFA) compared to other previous optimization algorithms (i.e., PSO, DPSO, FA, CPA, ReDE, HRPSO, AHEFA, ANDE, ECBO-Cascade, BB-BC, HS, and CPA) to examine their effectiveness.

5. CONCLUSION

This study presents a comprehensive survey on the application of metaheuristic algorithms to optimization problems in civil and structural engineering Reliability, and probabilistic based optimization research are not considered in this review. Moreover, only the journal papers published in the Scopus and ISI indexed journals have been included in this work. The selected structural optimization papers are categorized into three main subfields as truss optimization, frame optimization, and miscellaneous applications. In all the problems, optimization algorithms have been utilized to find the optimal design and minimize some measure of cost (such as the amount of material, operational cost, labor cost, or environmental impact). Based on the reviewed papers, truss design typically is focused on size, shape, or topology optimization, either considered independently or simultaneously. Frame optimization is focused on determining the optimal size of each element in the structure. There are a few studies that focused on the topology optimization of braces in frames. The miscellaneous optimization category includes the optimum design of steel, concrete, and composite structures. In all the structural optimization problems, several constraints were applied to the design procedure to provide adequate strength, stability, and serviceability.

As a whole, the number of publications on civil engineering optimization has increased over the last few decades, with the majority of the research focused on problems in structural and geotechnical engineering. In most cases, the design and analysis of these systems must satisfy guidelines and specifications defined by local building codes. It can be seen that in the initial studies, much simpler cases with a lot of simplifications were studied. In early studies, only limited or simplified conditions from building codes were incorporated into design procedures. However, in the course of time, as more robust state-of-art algorithms were developed, studies included more complex cases with more realistic, code-based constraints. Trends in current research have focused on updating benchmark problems, applying new algorithms, and improving computational efficiencies through different strategies such as applying various constraint handling approaches and strengthening the local and global searches by hybridization.

In general, most studies used basic statistical measures, including minimum, maximum, mean, median, and standard deviation when evaluating the performance of algorithms. In some cases, convergence rate history and diversity metric were utilized as additional features to measure the efficiency of some algorithms. All of these indicators are used to measure the robustness and computational efficiency of optimization algorithms.

One characteristic of real-world problems from the engineering perspective is that most projects have several different conflicting goals. It is vitally important to reach a balance and trade-off between different objectives to develop the best possible design. These problems could be addressed through bi- and multi-objective optimization.

Based on the work presented in this review, the following are research areas that may be addressed in future studies to close existing gaps:

(1) Developing benchmark problems that incorporating realistic conditions and limitations from building codes and consider any concerns of practising engineers

(2) Automating the design of large-scale structures that currently available in the literature

(3) Find the best possible formulation of an engineering problem to be optimized more effectively. One example could be using a semi-independent variable, introduced in Gandomi, Deb, Averill, Rahnamayan, & Omidvar (2019).

(4) Embedding engineering knowledge into population-based algorithms in order to narrow down the search space and boosting the optimization process.

(5) Informing constraint handling methods with engineering and domain knowledge to handle mechanical and geometrical constraints more efficiently.

(6) Since finding a feasible solution could be challenging in engineering practice, adopting engineering problems with constraint handling to more efficiently searching the feasible solution would be very beneficial (Gandomi & Deb, 2020)

(7) Application of hybridization methods that are very efficient in boosting the performance of optimization algorithms for certain categories of problems

(8) Development of more sophisticated metrics for optimization algorithm performance

(9) Continuing work on bi- and multi-objective optimization problems that provide more real-world designs.

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