Chapter

Overview of Multi-Objective Optimization Approaches in Construction Project Management

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Abstract

The difficulties that are met in construction projects include budget issues, contractual time constraints, complying with sustainability rating systems, meeting local building codes, and achieving the desired quality level, to name but a few. Construction researchers have proposed and construction practitioners have used optimization strategies to meet various objectives over the years. They started out by optimizing one objective at a time (e.g., minimizing construction cost) while disregarding others. Because the objectives of construction projects often conflict with each other, single-objective optimization does not offer practical solutions as optimizing one objective would often adversely affect the other objectives that are not being optimized. They then experimented with multi-objective optimization. The many multi-objective optimization approaches that they used have their own advantages and drawbacks when used in some scenarios with different sets of objectives. In this chapter, a review is presented of 16 multi-objective optimization approaches used in 55 research studies performed in the construction industry and that were published in the period 2012–2016. The discussion highlights the strengths and weaknesses of these approaches when used in different scenarios.

Keywords: construction project management, multi-objective optimization, evolutionary algorithms, swarm intelligence algorithms, analytic network process, nature-based algorithms, Hungarian algorithm, mixed-integer nonlinear programming, hybrid approaches

1. Introduction

The main objective of the construction industry is to directly and indirectly provide people's daily needs. Mostly, a construction project involves the use of different resources (e.g., machinery, materials, manpower, etc.) to produce the final product (e.g., a building, a bridge, a water distribution system, etc.) that serves the targeted users' needs. The difficulties that are met in construction projects include budget limitations, contractual time constraints, safety and health issues, sustainability ratings, local building codes, the desired level of quality, to name but a few. Consequently, a construction project has multiple objectives including maximum productivity, minimum cost, minimum duration, specified quality, safety, and sustainability. Making decisions is difficult when one wants to reach the optimal solution for a combination of objectives.

Construction practitioners have been using single-objective optimization strategies to meet the desired level of construction objectives. However, because the multiple objectives of construction projects often conflict with each other, single-objective optimization does not offer practical solutions, as optimizing one objective would often adversely affect the other objectives that are not being optimized. As a result, some projects fail to meet some of the objectives. In order to avoid such failures, researchers have developed tools that can help efficiently manage construction projects and achieve the required objectives. These tools include many multi-objective optimization approaches, each of which has its own advantages and drawbacks when used in some scenarios with different sets of objectives.

A review is presented in this chapter of the various multi-objective optimization approaches used in recent studies in the construction industry to highlight the strengths and weaknesses of these approaches when used in different scenarios.

2. Overview

A total of 55 studies that applied multi-objective optimization methods in the construction industry are reviewed in this chapter. To avoid overlapping and redundancy of reviews with Evins' work [1], the review in this chapter includes only the recent studies which were published in the period late 2012 to early 2016. Evins [1] covered the period of 1990 to late 2012 and conducted a review of the studies that applied optimization methods in sustainable building design.

The 55 studies are reviewed relative to (1) the optimization method, (2) the project phase, (3) the optimization problem, (4) the type and number of targeted objectives, (5) the example used to test a model, and (6) the comparison with other methods when applicable.

The number of optimization methods found in the review of the 55 papers was 16. These 16 methods and their usage frequency are presented in **Figure 1**, which shows that NSGA-II is the most used method (14 times) followed by a hybrid method (12 times) which pairs two or more methods for the optimization process. The acronyms in this figure are spelled out in **Table 1**.

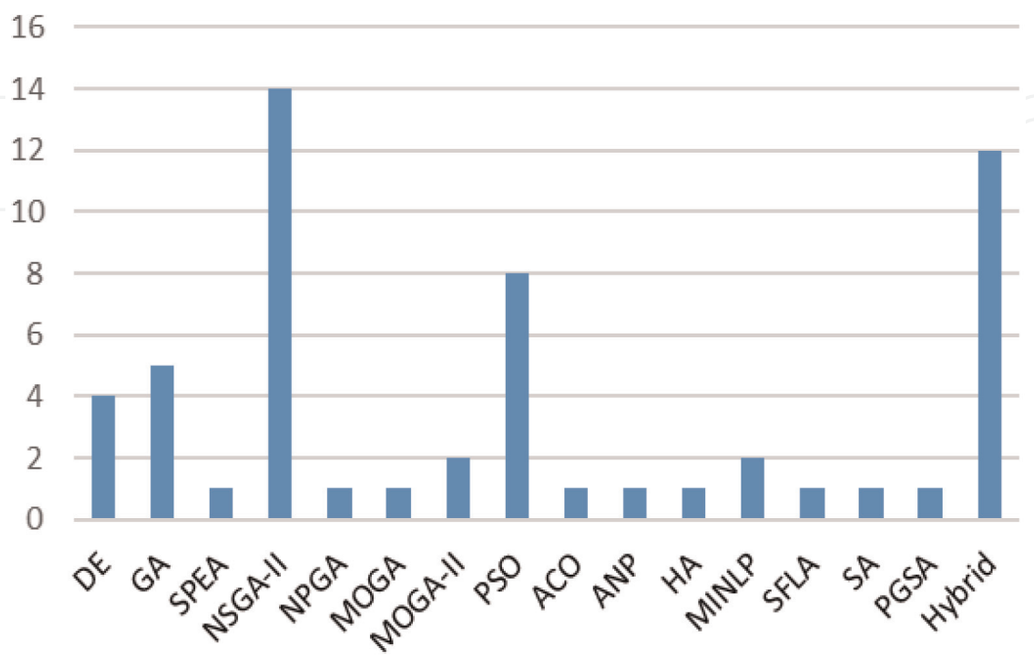

Figure 1.
Frequency of methods used in literature.

Optimization method	Number of objectives					
	2	3	4	5	6	7
Genetic algorithms (GA)	2	3	—	—	—	—
Differential evolution (DE)	1	3	—	—	—	—
Strength Pareto evolutionary algorithm (SPEA)	—	1	—	—	—	—
Non-dominated sorting genetic algorithm-II (NSGA-II)	8	6	—	—	—	—
Niched Pareto genetic algorithm (NPGA)	—	1	—	—	—	—
Multi-objective genetic algorithm (MOGA)	1	—	—	—	1	1
Particle swarm optimization (PSO)	3	3	—	2	—	—
Ant colony optimization (ACO)	1	—	—	—	—	—
Analytic network process (ANP)	—	—	1	—	—	—
Shuffled frog-leaping algorithm (SFLA)	—	1	—	—	—	—
Simulated annealing algorithm (SA)	1	—	—	—	—	—
Plant growth simulation algorithm (PGSA)	1	—	—	—	—	—
Hungarian algorithm (HA)	1	—	—	—	—	—
Mixed-integer nonlinear programming (MINLP)	2	—	—	—	—	—
Hybrid methods	6	6	—	—	—	—
Total (56 methods)	27	24	1	2	1	1

Table 1.
Number of objectives used in the literature.

These optimization methods were used to tackle different numbers of objectives at a time. The number of objectives that was simultaneously optimized ranged between 2 and 7. The most common number of objectives in a study was 2 or 3 objectives (27 and 24 times, respectively) distributed by methods as shown in **Table 1**. The least common number of objectives considered in a study was 4, 6, and 7 (one time each). It should be noted that one of the 55 papers used two optimization methods, i.e., NSGA-II and PSO. Therefore, the total number of methods used in the 55 papers is 56.

As expected, the large majority of the studies optimized two or three objectives that concern most practitioners. The number of times the objectives were used is presented in **Table 2**. Among the objectives used in the 55 papers, cost was the mostly optimized, accounting for 93% (51 times) of the total number of studies, duration was the second most optimized objective accounting for 42% (23 times), and the energy and environment category was the third most optimized with 31% (17 times). The rating system score was used only 3 times, i.e., in only 5% of the studies, which represents the least optimized objective.

3. Multi-objective optimization methods used in recent construction-related studies

3.1 Genetic algorithms (GA)

GA is one of the popular evolutionary algorithms used by researchers. GA uses the concept of chromosomes to present the possible solutions in these chromosomes' strings [2]. The different aspects of each solution are positioned into the slots

Objective	Number of times objective used in studies
Cost	51
Duration	23
Quality	7
Resources	7
Energy and environment	17
Thermal	13
Safety	6
Rating system score	3
Other	23

Table 2.
Number of times the objectives were used in the 55 studies.

which form the string [3]. A new set of solutions are found by the crossover between two strings (parent strings), and the new strings (children) will inherit the best features of the parent strings.

In construction-related fields, GA has been applied in many multi-objective optimization problems. For example:

- GA was used to improve sustainability in housing units. Karatas and El-Rayes [4] used GA in a single-family housing unit to optimize operational environmental performance, social quality of life, and life cycle cost. They used 33 decision variables in the model and computed in 47.5 hours 210 near-optimal solutions within a large search space of configurations and decisions (more than 2.6 quadrillion).

- GA was used to solve conflicting objectives in construction scheduling. For instance, Agrama [5] used GA to optimize building schedules. The author analyzed a 5-storey building and used nine scenarios for the weights of three objectives: project duration, total actual crews, and total interruptions for all activities. The model was implemented in Excel (Evolver) and solved by GA. In addition, it was found that the model performs consistently and can be used with both the critical path and line of balance methods. Moreover, the results obtained were identical to those in the literature but required less time and effort. Alternatively, Aziz et al. [6] introduced a method that combines CPM with GA to optimize the utilization of resources for mega construction projects in terms of time, cost, and quality. An 18-activity schedule was tested using the proposed method. To avoid complexity, the five decision variables which were construction materials, crew formation, crew overtime policy, machinery efficiency, and contractor class were all combined into a single decision variable called resource utilization. In this test, 305 optimal solutions were identified. Additionally, the results showed that the model outperformed the approach used by Feng et al. [7] with the same case example.

- GA was used in managing site operations. For example, in material logistics, Said and El-Rayes [8] presented an example of a 10-storey building consisting of 107 activities with four temporary facilities. The aim of the model was to minimize total construction logistics costs (Eq. (1)) and minimize project schedule criticality (Eq. (2)).

$$Min\ TLC = OC + FC + SC + LC \tag{1}$$

$$Min\ SCI = \frac{1}{N'} \times \sum_{i=1}^{N'} CI_i = \frac{1}{N'} \times \sum_{i=1}^{N'} \frac{SS_i - ES_i}{TF_i} \tag{2}$$

where, TLC = total logistics costs; OC = ordering cost; FC = financing cost; SC = stock-out cost; LC = layout cost; SCI = schedule criticality index; N' = number of noncritical activities; CI_i = criticality index of activity i; SS_i = scheduled start time of activity i; ES_i = early start time of activity i; and TF_i = total float of activity i.

Because the search space is large and the problem is complex, the authors justified the use of a GA model that involves 152 decision variables and 462 constraints. The model generated 361 optimal solutions. For equipment management problems, Xu et al. [9] proposed dynamic programming-based GA because they believed it would be capable of solving this type of problem more efficiently than traditional methods. The goal of the method was to minimize the project's total cost and maximize equipment operations such that in case of equipment failure there would be an equipment available. Moreover, to make the method more reliable, the failure rate of the equipment was considered a fuzzy variable. An actual hydropower project in China was selected to test the model. Under the same environment, the proposed algorithm performed better in searching than the standard GA.

In summary, there is evidence that GA can optimize different objectives in the construction industry in the field of scheduling, sustainability, and site operation.

3.2 Differential evolution (DE)

The DE approach is efficient and has low algorithmic complexity. There is also some evidence of its effectiveness in tackling problems of continuous optimization with different types of constraints and functions [10]. The members of the population in DE use floating-points which identify each member's direction and distance [11]. Therefore, the main concept behind the DE approach is that it creates a new population member with a vector that has the difference between two members' vectors; that process is done by the mutation and crossover processes [12].

DE has proved its effectiveness in complex planning and scheduling problems by optimizing cost and time in addition to quality, environmental impact, or resources. For example:

- Narayanan and Suribabu [13] applied DE to assist contractors in optimizing their plans for subcontracting in terms of cost, time and quality. To examine the model, they used a 7-activity and an 18-activity project. By comparison, the DE model generated better solutions than ant colony optimization (ACO) for cost in the first case, and for cost and time in the second case.

- Alternatively, Cheng and Tran [14] used a two-phase DE model on a 37-activity warehouse project to minimize total project cost and duration, while accounting for resource constraints. In the first phase, a multiple objective DE model was used to find the optimal tradeoff between time and cost in construction activities. Based on the solution obtained in the first phase, the best schedule was found within resource constraints in the second phase. A comparison of the results showed that the developed model outperformed three evolutionary algorithms: DE, particle swarm optimization (PSO) and NSGA-II.

- Subsequently, Cheng and Tran [15] proposed opposition-based multi-objective DE. The aim was to optimize construction products in terms of cost, time and environmental impact. The model used opposition-based learning to increase precision and convergence speed. A tunnel project consisting of 25 activities was used to test the model. The proposed model was superior compared to NSGA-II, PSO, and DE algorithms. The exact approach also outperformed these algorithms in a similar study conducted by Cheng and Tran [16].

- The goal of the Cheng and Tran [16] study was to minimize project time (Eq. (3)), project cost (Eq. (4)), and the utilization of resources (Eqs. (5) and (6)) in overtime shifts.

$$Min\ T = \sum_{n=1}^{l} T_n^{S_n} = \mathrm{Max}_{\forall n}(\mathrm{ES_n} + D_n) \tag{3}$$

$$Min\ \mathrm{C} = \sum_{n=1}^{N} Cost_n^{S_n} \tag{4}$$

$$Min\ LHEN = LHE + LHN(1 + W)\ if\ \mathrm{SS} = 3\ (three - shift\ system) \tag{5}$$

$$Min\ LHNE = LHE\ if\ \mathrm{SS} = 2\ (\mathrm{two} - shift\ system) \tag{6}$$

where in Eq. (3), $T_n^{S_n}$ is the duration of the activity $n\{n = 1, 2, \ldots, l\}$ on the critical path for a specific option of resources (S_n); l is the total number of critical activities on a specific critical path; ES_n is the earliest start of activity n; D_n is the duration of activity n. In Eq. (4), $Cost_n^{S_n}$ is the total cost which includes direct and indirect cost of activity n for a specific option of resources (S_n); N is the total number of activities. In Eqs. (5) and (6), LHE is the total number of evening shift work hours and LHN is the total number of night shift work hours. Because risks faced in night shiftwork are typically higher than in other shifts, W is the defined weight that represents the relative importance of minimizing LHN.

A 15-activity and a 60-activity project were used to test the model. In just one run, the model was capable of finding Pareto-optimal solutions to solve the objectives of the problem.

It can be concluded that the DE algorithm is capable of optimizing several objectives of time, cost, resource utilization, and environmental impact. Moreover, as DE and its variations successfully optimized those objectives, they also surpassed ACO, PSO, and NSGA-II in construction scheduling optimization.

3.3 Strength Pareto evolutionary algorithm (SPEA)

SPEA works by archiving the non-dominated solutions found in the Pareto-front at every iteration. Then, based on the number of solutions it dominates, each solution in the archive is ranked with a strength rate [10, 17].

In dealing with scheduling problems, SPEA was proposed by Elazouni and Abido [18] to optimize the three conflicting objectives of maximizing profit and minimizing required finance and resource idle days. The study used two examples from the literature to test the efficiency and scalability of the model. In the first example, the model was tested for its effectiveness in solving a 9-activity project. The model confirmed its robustness by achieving 50 identical solutions. By searching these solutions using a fuzzy based method, the top ones were selected. In the second example, an 18-activity project was used to assess the model's scalability.

Four solutions (maximum profit, minimum finance, minimum resource idle days, and the top compromised solution) were drawn from the 48 solutions obtained in the Pareto-optimal front. Clustering the Pareto solutions set was used to keep it within a manageable size. Nevertheless, because of the clustering, this method may result in the loss of some extreme Pareto solutions.

By optimizing the construction objectives of profit and resources, SPEA has verified its efficiency in the scheduling field. However, the clustering method proposed by Elazouni and Abido [18] should be avoided when using SPEA in order to avoid the elimination of some extreme Pareto solutions. New clustering approaches should be explored in upcoming studies.

3.4 Non-dominated sorting genetic algorithm-II (NSGA-II)

One of the most powerful tools of genetic algorithms is NSGA-II. It uses the non-dominated sorting for the solutions in the population. The non-dominated solutions are ranked at every iteration, and are excluded from the population in every iteration afterwards. In addition, in each ranked-solution set, the solutions are compared to each other by their crowding formation. In the crowding step, the position of a single solution is measured by its distance from the adjacent solutions' points, and based on its distance, the solution is assigned with a rank, as the best ranks start from the shortest distance to the longest one [10].

NSGA-II has been used to solve multi-objective problems aimed at the optimality of energy consumption and sustainability in buildings. For instance:

- Eliades et al. [19] used NSGA-II to optimally select the installation locations for indoor air quality sensors, in terms of number of sensors, and average and worst-case impact damage while considering the building's usage in the parameters. A simple 5-room building and a 14-room house were studied to illustrate the performance of the proposed model, with 5 and 2310 contamination scenarios, respectively. Grid and random sampling were used to construct the contamination scenarios, and the multi-zone building program CONTAM simulated them.

- In zero-energy-building (ZEB), Hamdy et al. [20] used a modified version of NSGA-II to find solutions for the optimal cost and nearly zero energy building performance with respect to the guidelines of European directives for the energy performance of buildings. Due to the large number of combinations, the solution space was divided into three stages. The total number of combinations (179, 712) in the first stage were searched in 800 runs.

- Huws and Jankovic [21] took into account future weather changes that could affect retrofitting strategies. These weather changes may eventually unsettle the performance of zero-carbon buildings by increasing the carbon emissions or cost, or in some cases a combination of these may create thermal discomfort. For that reason and to achieve optimal solutions for retrofit, environmental, social, and economic constraints were considered in optimizing the objectives of minimizing cost, CO_2, and thermal discomfort. A simple 60 m^2 box model was created using the DesignBuilder program. DesignBuilder and JEPlus were used to perform the optimization process. NSGA-II within JEPlus was used for its capability of searching a large solutions space, and to avoid being stuck in a local suboptimum. The results indicated that there is an applicable alternative for both current and future weather.

- In sustainability for low-income housing, Marzouk and Metawie [22] incorporated NSGA-II with BIM to assist the Egyptian government find solutions that best optimize those objectives. The BIM model was created using Revit. The model was defined based on the quantities and properties of the materials extracted from the BIM model. These quantities helped to find the different solutions in terms of project cost, duration and maximum LEED points. Construction productivity and cost were determined using a 44-activitiy low-income housing building. Moreover, LEED points were calculated through five credits chosen from the materials and resources category.

- Kasinalis et al. [23] studied the improvement of indoor environment while reducing the energy consumption in climate adaptive building shells, and quantified the impact of using seasonal adaptation façade on those objectives. The example of an office zone model was used to evaluate the approach. The combination of daylight and energy simulations were utilized with NSGA-II to perform multi-objective optimization on that example. The optimization process considered six design parameters for the façade. The results showed that using a seasonal adaptation façade with these parameters is more efficient than a non-adaptive façade, since it can save up to 18% of energy consumption and enhance the quality of the indoor environment.

- Inyim et al. [24] approached the problem of building components and material selection by using (SimulEICon) a BIM tool that simulates the environmental impact in buildings. The optimization process of time, cost and CO_2 emissions was performed by NSGA-II. The case study was an actual zero net energy house. The model considered 16 activities and 185 building components. It was found that some of the combinations of components suggested by SimulEICon matched the original component combinations used in the existing house. However, SimulEICon lacked the ability to account for more than three objectives.

- Carreras et al. [25] introduced an approach for selecting the thickness of insulation material for building shells. The objective of the study was to select the best option for the insulation that optimizes the costs (Eq. (7)) and environmental impacts (Eq. (8)) associated with energy consumption.

$$Min\ Cost_{total} = Cost_{cub} + Cost_{elec\_n} \tag{7}$$

$$Min\ Imp_{total} = Imp_{cub} + Imp_{elec} \tag{8}$$

where $Cost_{total}$ is the total cost, $Cost_{cub}$ is the cost of the materials used; $Cost_{elec\_n}$ is the cost of the electricity consumed over the operational phase (n years); Imp_{total} is the total environmental impact; Imp_{cub} is the total impact of the materials used; and Imp_{elec} is the impact of the consumed electricity over the operational phase.

The authors used the example of a cubicle without insulation to compare the different results collected from using two cases of insulation. In the first case, similar thicknesses were used over the cubicle, while in the second case, different thicknesses were considered. Three materials were considered in the insulation selection process (polyurethane, mineral wool, and polystyrene). From the results, the polyurethane insulation was the least costly solution, whereas the optimal environmental impact solution was mineral wool insulation. The proposed methodology could improve the costs and environmental impacts by almost 40% when compared to a non-insulated cubicle.

Site operations and planning problems were also tackled using NSGA-II. For instance:

- Fallah-Mehdipour et al. [26] applied NSGA-II to solve two tradeoff problems, time-cost and time-cost-quality, respectively. To validate the proposed method, an 18-activity and a 7-activity work schedule were utilized. Additionally, multi-objective PSO was applied. The results showed that NSGA-II was superior to multi-objective PSO.

- In managing and storing materials in a construction site, Said and El-Rayes [27] presented an automated module, which imports its data from BIM files and historical schedule data. A module in the system was named construction logistics planning (CLP) and aimed to minimize the cost of logistics and the criticality of the schedule. These objectives were optimized by tackling four decision variables using NSGA-II. An application model of a 10-storey building project was used to apply the optimization process. The automated system generated better results compared to using CLP alone. A total of 361 optimal solutions were produced within 65 hours. Unlike CLP, which considered the utilization of exterior site space and disregarded the interior one, the system generated the solutions accounting for both spaces.

- In site operations, Parente et al. [28] proposed NSGA-II to optimize the allocation of compaction equipment within the criteria of cost and time associated with earthworks in large infrastructure projects. Additionally, linear programming was used for the allocation of the remaining equipment such as trucks and excavators. The proposed method which uses an actual construction site as a case study proved to be superior to the S-metric selection evolutionary algorithm as well as manual allocation.

NSGA-II was used to find solutions in problems involving upgrade plans for water networks and slum areas. For example:

- Creaco et al. [29] divided the construction phases of a water network upgrade into four phases, considering the different phases of upgrades to the water network in a 100-year plan of possible upgrades. NSGA-II was used with a model of six network nodes and eight pipe laying locations to find the optimal solutions within the two objective functions: maximizing the minimum pressure and minimizing the cost, while the pipe diameters are acting as the decision variables. The proposed approach provided better results than the studies that used single phasing, by giving the optimal solution for maintaining the water distribution and pressure quality through the time of upgrade phases. In a similar study, Creaco et al. [30] proposed the use of NSGA-II while considering an additional factor to the study, which was the uncertainty of water demand. The authors determined the uncertainty using a probabilistic approach. Based on an example with 26 network nodes and 31 pipe laying locations. The probabilistic approach was compared with the deterministic approach used by Creaco et al. [29]. The results revealed that the solutions obtained by the probabilistic approach had higher costs than the solutions of the deterministic approach, especially in the first phase. However, the probabilistic solutions generated better results in terms of costs when the comparison was about the worst-case scenario.

- In uneven ground levels of slum areas, El-Anwar and Abdel Aziz [31] used an example of nine-zone slum area with a population of 2770 families to select the optimal upgrade plan. The optimization process involved three objectives: maximization of benefit of proposed upgrading projects, minimization of costs and socioeconomic disruption for the families. Due to its superiority over other GAs in solving multi-objective problems, NSGA-II was selected to solve the problem in which it generated 2000 solutions in less than 1 minute. Nevertheless, the time schedules module was not included in the model hence affecting its robustness.

- Brownlee and Wright [32] analyzed the relationship between design objectives and the effectiveness of design variables on the design objectives by using NSGA-II. They sorted the objectives by simple ranking. The approach was performed on a five-zone building with only two design objectives. The objectives to be minimized were total annual energy use and capital cost, and the design variables were 52 in total. Forty-nine solutions were generated using NSGA-II. However, the proposed approach failed to discriminate the distance variables which are the variables that measure the sets from the true Pareto-optimal set from the floating variables which are the variables that have no effect on the objective function.

As the above-cited studies show, the NSGA-II proved its capability in optimizing for scheduling, urban planning, infrastructure, sustainability, energy and environmental design, and resource management. In addition to its superiority over other GAs, NSGA-II has also outperformed other methods in some fields. One of those is the multi-objective PSO applied to scheduling problems.

3.5 Niched Pareto genetic algorithm (NPGA)

The tournament selection among a population's individuals and Pareto dominance are the two basic ideas of NPGA's process. The selection process is based on the dominance of two randomly selected individuals from the population. To determine which individual of these two is dominant over the other, another set of individuals are picked and used to go against the two competing individuals, to examine the level of the two competing individuals in dominating each individual of the set. The winning criterion is defined by Pareto-front dominance. Therefore, one of the two competing individuals is selected if the other is dominated by one of the individuals in the set [33, 34].

Kim et al. [35] used NPGA to optimize cost, time and resource utilization. They optimized the three objectives at the same time. To test the performance of the method, they conducted two case studies. The first case had 11 activities, and measured the method's efficiency in solving the tradeoff problem between cost and time. In addition to the objectives in the first case, the second case extended the examination of the approach by including the resource-leveling index as an objective. The results showed that this method could provide decision makers with different solutions to enable them selecting the one that meets their preferences.

3.6 Multi-objective genetic algorithm (MOGA)

MOGA is an advanced version of traditional GA. The difference between MOGA and GA is the individual fitness assignment, while the remaining steps are followed as in GA. In MOGA, ranking is assigned for each individual in the population. The rank is assigned based on individual's dominance, if the individual is not dominated

by another individual in the population then it is assigned with the rank of one. But if an individual is dominated by other individuals then it is assigned with a rank corresponding to the total number of dominating individuals plus one [36].

- MOGA has shown its capabilities in achieving optimal structural design. For example, Richardson et al. [37] tackled the design problem of an x-bracing structural system for a building façade. Minimizing the cost of the bracing connections and the effectiveness of the bracings were the objectives under the multi-objective topology optimization process (Eq. (9)).

$$\min_{x} f(x) = \left(f_1, f_2\right) \tag{9}$$

where f_1 is the cost objective function expressed in Eq. (10), x is the variable vector of length n, and f_2 is the relative tier deflection objective function expressed in Eq. (11).

$$Min\ \mathrm{f}_1 = \sum_{i=1}^{n} a_i.x_i \tag{10}$$

$$Min\, f_2 = \max\left\{\frac{|d_1|}{h_1}, \frac{|d_2 - d_1|}{h_2}, \frac{|d_3 - d_2|}{h_3}\right\} \tag{11}$$

where a_i is a weighting coefficient related to the grouping of components based on symmetry; x_i is the topology variable associated with bracing(s) i; h_j is the height of tier j; and d_j is the measured deflection of tier j from rest position.

While the constraints change as the design progresses, the proposed approach dynamically adapts to those constraints. Museum façades were picked to test the performance of the optimization method.

- In reducing the energy consumed and environmental impact in buildings, Baglivo et al. [38] have used an improved version of MOGA (MOGA-II) on combinations of sustainable building materials for external walls of zero energy buildings, to achieve the best optimal solutions in balancing the life cycle cost and energy consumption. The materials were tested according to their thermal characteristics based on the Mediterranean climate. The assessment of material combinations was carried on six thermal-related objectives. The study concluded that the best selection of materials for external walls was by placing the insulation coating on the external side of the wall, while placing the high internal capacity material on the interior side. Similarly, Baglivo et al. [39] have conducted a study that added one more objective to the same six objectives.

3.7 Particle swarm optimization (PSO)

The pattern of flocking birds and fish was the inspiration of PSO. In PSO, a set of solutions is called swarm, while a solution is called particle [26]. The particles are positioned in a D-dimensional search space. In each step, every particle changes its velocity to move toward the best solution and toward the global best solution [40].

Different issues of construction engineering and management were tackled by PSO. Some studies proposed PSO to solve site planning problems. For instance:

- Xu and Li [41] proposed permutation-based PSO to solve the planning problem of a dynamic construction site layout, in which ordinal numbers assigned to the

particles were used to present the potential solutions. The objectives considered in the problem were the layout cost and the environmental and safety accidents. Since the study accounted for uncertainty, fuzzy random variables were included in the model. The model used the example of 14 temporary facilities in a hydropower project to evaluate its efficiency. The proposed approach proved to be more realistic than existing traditional approaches.

- Xu and Song [42] approached the problem of unequal-area departments in dynamic temporary facility layout using position-based adaptive PSO. By using the facilities' coordinates as base for its model, the optimization process aimed at minimizing the total distance between adjacent facilities and the resulting costs associated with rearrangement and transportation, in which the transportation costs were considered as fuzzy random variables. The modified PSO was evaluated through a case study of a large-scale hydropower construction project. The proposed method showed better performance in obtaining optimal solutions when compared to standard PSO and GA.

- Li et al. [43] proposed a modified PSO to achieve optimal solutions for dynamic construction site layout and security planning. The study approached the problem using the Stackelberg Game theory, in which the construction manager (the leader) must set up the layout and secure the facilities, then the attacker (the follower) has to create the maximum possible economic damage to the facilities. Bi-level multi-objective PSO was proposed to solve the problem. The method was implemented in a hydropower construction project to test its performance. The proposed method outperformed GA in achieving optimal solutions.

PSO has also been used in tackling different objectives in the maintenance of deteriorating structures. For example:

- Yang et al. [44] approached the problem of life cycle maintenance planning for deteriorating bridges using PSO with Monte Carlo simulation (MCS). Cost, safety and condition levels were the main objectives in the maintenance problem. Uncertainties in the maintenance cost, work effects of maintenance, and the structure' deterioration rate were also accounted for in the study. Parallel programming was used to minimize the computing time to solve the problem. Yang et al. [44] considered three paradigms in the programming process, namely master-slave, island, and diffusion. In each paradigm, the computers have a different set up to run MCS in parallel. From the analysis, the island paradigm surpassed the other two in terms of solution quality. By comparison, the multi-objective PSO algorithm outperformed NSGA-II.

- Chiu and Lin [45] proposed PSO to achieve the optimal strategies in maintaining reinforced concrete buildings. The authors considered five objectives in the study, which are life cycle cost, failure possibility, spalling possibility, maintenance rationality, and maintenance times. Assessment models of probabilistic effects were employed to observe the effects of maintenance strategies on the damage index. The four processes of analysis of deterioration, assessment of seismic performance, forming maintenance strategies, and multi-objective optimization were performed in the proposed maintenance strategy. The evaluation was completed using a case study of a four-story reinforced concrete school building.

Some researchers used PSO to tackle different design objectives and constraints to achieve optimal sustainable design solutions. For instance:

- Decker et al. [46] have proposed a PSO algorithm to reach better design solutions in timber buildings. In addition to architectural, energy and environmental constraints, the study added structural constraints. The optimization process was in terms of energy needs, thermal discomfort, floor vibration, CO_2 emissions, and embodied energy. To minimize computing time, the simulation model was transformed using a metamodeling procedure. A three-story office building was used as a case study to validate the proposed approach.

- Chou and Le [47] used PSO in combination with MCS to attain the optimal solutions for building designs in terms of minimizing duration (Eq. (12)), cost (Eq. (13)), and CO_2 emissions (Eq. (14)).

$$Min\ F_{dur} = \mathrm{ES}_{\mathrm{fin}} + \sum_{i=1}^{n} ES_i \tag{12}$$

$$Min\ F_{cost} = \sum_{i=1}^{n} W_i.COST_i \tag{13}$$

$$Min\ F_{CO_2} = \sum_{i=1}^{n} W_i.FC_i \tag{14}$$

where F_{dur}, F_{cost}, and F_{CO2} represent project duration, project cost, and CO_2 emissions, respectively; ES_{fin} is the early start of the finish activity; ES_i is the early start of activity i; $COST_i$ is the unit cost of activity i; n is the number of activities; and FC_i is the amount of CO_2 emitted to complete a unit of work of activity i.

In addition to PSO, a probabilistic method was applied to handle the uncertainties associated with the objectives of the study. The case study of a 12-activity roadway pavement project was used to evaluate the performance of the proposed method.

In sum, PSO proved its effectiveness in tackling the multi-objective optimization problems in different construction engineering and management areas such as site planning, maintenance of a structure, and sustainability issues. It was found that PSO's performance was superior compared to traditional approaches such as GA and advanced approaches such as NSGA-II.

3.8 Ant colony optimization (ACO)

The stimulus in discovering the ACO algorithm was the movement of ants and their trails of pheromones when searching for food. In the ACO process, each solution is connected to a route that is searched by an ant. Each solution's quality is evaluated by the quantity of pheromones that were deposited on the route by ants. The amount of pheromone left on a route indicates the closeness to the optimal solution. The chance of finding the shortest route increases for an ant as the amount of pheromone on a route increases [48].

The proximity and number of construction facilities and other resources on a construction site could contribute to an increase in cost and safety issues. Ning and Lam [49] developed a modified ACO model to tackle safety and cost problems within a site layout of irregular shape. The model was aimed to minimizing safety/

environmental concerns by reducing the occurrence of accidents (Eq. (15)) as well as minimizing the total handling cost between facilities by reducing the cost associated with resource exchanges among facilities (Eq. (16)).

$$Min\, f_1 = \min \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{l=1}^{n} \sum_{k=1}^{n} S_{ij} d_{kl} x_{ik} x_{jl} \tag{15}$$

$$Min\, f_2 = \min \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{l=1}^{n} \sum_{k=1}^{n} C_{ij} d_{kl} x_{ik} x_{jl} \tag{16}$$

where S_{ij} is the closeness relationship value for safety/environmental concerns between facilities i and j; C_{ij} is the total closeness relationship value for the total handling cost between facilities i and j; d_{kl} is the distance between facilities k and l; x_{ik} means when facility i is assigned to location k; and x_{jl} means when facility j is assigned to location l.

The optimization process started by dividing the site layout into a grid. The grid units were selected based upon the dimensions of the facilities. Then, the ACO model was used to assign the different facilities on the site grid. To test the soundness of the model, a residential project composed of four buildings was selected. The proposed grid strategy reduced the complexity of the computational process.

3.9 Analytic network process (ANP)

Like the analytic hierarchy process, decision makers utilize ANP to solve multi-criteria decision problems. The AHP uses a one-way top-down hierarchal process for its components such as goals, criteria, and alternatives [50]. The ANP which is a generalized version of AHP uses a network for some problems when their components have interdependencies between them. The flow in the ANP's network is open and allows any component to interact with another regardless of their levels, which is not possible in AHP [51].

Liang and Wey [52] proposed an ANP model to optimally select government projects by accounting for the limitation of resources along with uncertainties and socioeconomic factors. In order to test the model's effectiveness, seven projects in a nation-wide highway improvement project were used as an example. In the example, construction costs were determined by probability distributions and seven criteria were used to evaluate the projects. Moreover, since the model involves the use of multiple criteria, ANP was combined with MCS to make the selection of projects based on the solutions achieved by solving the multi-objective problems. ANP ranking was used to rank each project based on its value of priority among other projects. A cost-benefit approach was used to optimize the selection of projects based on the existing budget plan and the allocation of remaining budget to fund a project in full. The four objectives within these two problems were minimization of cost (Eq. (17)) and the number of project managers (Eq. (18)), and the maximization of project ranking (Eq. (19)) and the number of completed projects (Eq. (20)).

$$Minimize\ modified\ mean\ absolute\ deviation\ of\ cost = Min\ \frac{\sum_{i=1}^{n} \sum_{j=1}^{m} y_{ij}^{+}}{nm} \tag{17}$$

$$Minimize\ number\ of\ project\ managers = Min\ \sum_{i=1}^{n} PMNO_i x_i \tag{18}$$

$$Maximize\ project\ ranking = Max\ \sum_{i=1}^{n} RANK_i x_i \tag{19}$$

$$Maximize\ number\ of\ completed\ projects = Max\ \sum_{i=1}^{n} x_i \tag{20}$$

where n is the number of projects; m is the number of scenarios; y_{ij}^{+} is the positive deviation of the cost of the scenario from the expected cost of the project; $RANK_i$ is the ranking given to project i based on the ANP computation; x_i is a binary variable which has a value of 1 if project i is selected, and 0 otherwise; and $PMNO_i$ is the number of project managers needed to complete project i.

3.10 Shuffled frog-leaping algorithm (SFLA)

The SFLA idea is based on frogs' behavior in their search to locate the largest quantities of food [53]. A single solution is represented by one frog [54, 55]. The frogs are divided into groups (memeplexes). Each memeplex of frogs performs a local search, and every frog has an idea which is affected by other frogs' ideas to improve the quality of the local search [56]. A shuffling process is performed to allow the memeplexes in exchanging information between them and create new memeplexes to ultimately improve their quality of search [53, 54, 56].

Improving the quality of the final product with limited resources is the ultimate goal of construction managers and planners. Time, cost, and resources play important roles in achieving this goal. Ashuri and Tavakolan [57] concurrently optimized three objectives: the duration expressed by sum of the durations of activities on the critical path, the project cost including direct and indirect costs, and resource allocation variations expressed in Eq. (21).

$$Min\ (SSR) = min\left(\sum_{k=1}^{TD}\sum_{n=1}^{S} R_{n,d}^{2}\right) \tag{21}$$

where $R_{n,d}$ is the number of the nth resource with n = 1, 2, … , S that is planned for use in day d with d = 1, 2, … , TD of the project duration.

To solve these problems, they used the SFLA model. In order to find feasible solutions to the problem at hand, the model accounts for the reallocation of resources and for activity interruptions and splitting. In addition, the authors made use of the advantages of PSO and the shuffling complex evolution algorithm, which helped the model achieve better solutions and converge more rapidly. A 7-activity and an 18-activity project were utilized to assess the efficiency of the model. Delphi was the coding environment for the model. Due to the complexity of the problem, the solutions obtained were near-optimal. However, the proposed model generated better solutions than other algorithms used prior to the study.

3.11 Simulated annealing algorithm (SA)

SA inherits its method from the movements of atoms within a material during the process of heating and then slowly cooling down [58]. In the optimization problem, the physical system's characteristics resemble the actual annealing process [10]. Talbi [10] listed the characteristics of physical annealing with their corresponding characteristics of the optimization problem. In physical annealing, temperature and speed of cooling down play important roles on the strength of metals. Deficiencies (metastable states) occur when cooling down speed is fast or

the temperature at the start is not high enough [59]. That means carefully setting up the temperature and cooling down speed is essential in escaping the local optimum —metastable state in physical annealing—and reaching the global optimum. A solution that is generated after an iteration is used, if feasible, to generate a new solution, but if the solution is infeasible, it is accepted only if it meets the probability criterion [10, 60]. The probability increases in obtaining an optimal or near-optimal solution when the annealing is slowed down [61].

To optimally design and construct a water distribution network, Marques et al. [62] proposed a model that used the SA algorithm combined with the EPANET hydraulic simulator. The objective was to minimize the cost of construction and operation including the initial and future costs, and to minimize violations in pressure as expressed in Eq. (22).

$$Min\ TPV = \sum_{s=1}^{NS}\sum_{t=1}^{NTI}\sum_{d=1}^{NDC}\sum_{n=1}^{NN}\max\{0;(Pdes_{\min,n,d} - P_{n,d,t,s})\} \tag{22}$$

where *TPV* is the total pressure violations; *NS* is the number of scenarios; *NTI* is the number of periods into which the planning horizon is subdivided; *NDC* is the number of demand conditions considered for the design; *NN* is the number of nodes; $Pdes_{min,n,d}$ is the minimum desirable pressure at node n for demand condition d; and $P_{n,d,t,s}$ is the pressure at node n at demand condition d for time interval t and in scenario s.

Eight scenarios were accounted for varying between three possible patterns of growth in the area: expansion, no expansion, and depopulation in a 60-year period. They split the 60-year duration of the plan into 320-year stages, and structured them into a decision tree to show the probability of the paths in each scenario. They used a 17-node distribution network to illustrate the model's efficiency. The decision variables included cost, diameters of pipes (eight diameters were considered), and carbon emissions produced during construction and operation (in terms of tons). The value of the objective function was not noticeably affected by the decision variable of carbon emission costs.

3.12 Plant growth simulation algorithm (PGSA)

The PGSA imitates the growth process of trees. The model's formulation for the optimization process in PGSA is based on the growth of plants [63]. It begins at the root then moves toward the light source (global optimum solution) to grow the branches [64]. A probability model is employed to form new branches which are used to guide the objective function toward the optimal solution [65].

To better minimize the losses and costs caused by an attack to the construction site and to increase the safety precautions to counter these attacks, Li et al. [66] used a bi-level model. The objectives of reducing attack-related cost and increasing facility productivity were considered at the upper level, in which the secured facilities were constrained by cost. The attacker, on the other hand, has the objective of reducing facility productivity, which is considered in the lower level. The formulation of the objective functions is as follows:

$$Max_{z_j} D = \sum_{j=1}^{N}\sum_{i=1,\ i\neq j}^{N}\sum_{k=1}^{5}\theta_{ij}p_k\mu_{ijk}^{r}d_{ij}s_j + \sum_{j=1}^{N}\sum_{i=1,\ i\neq j}^{N}\theta_{ij}d_{ij}z_j + \sum_{j=1}^{N}\sum_{i=1,\ i\neq j}^{N}\theta_{ij}d_{ij}(1-s_j)(1-z_j) \tag{23}$$

where D is the resource supply rate; z_j is 1 when facility j is secured and 0 otherwise; s_j is 1 when facility j is attacked and 0 otherwise; θ_{ij} is the weight of demand's importance; $0 \leq \theta_{ij} \leq 1$; d_{ij} is 1 when demand of facility i is served by facility j and 0 otherwise; p_k is the occurrence probabilities of the kth degree attack, $k \in \{1, \ldots, 5\}$; and μ^r_{ijk} is the mean value of the fill rate of facility j to facility i when facility j is attacked.

$$\mathrm{Min}_{z_j} C = \sum_{j=1}^{N} \sum_{k=1}^{5} p_k \mu^c_{jk} s_j + \sum_{j=1}^{N} M_j z_j \tag{24}$$

where C is the economic loss of defender; M_j is the cost of securing facility j; *and* μ^c_{jk} is the mean value of the economic loss when facility j is attacked.

Because integer programming made the problem complicated, the authors proposed PGSA. The model was applied on an actual hydropower project. Fifty runs were executed to achieve the optimal solution in less than 4 minutes. Even though the proposed model efficiently solved the problem, it did not top the list of algorithms. This study was the first study to apply PGSA on the problem of construction site security.

3.13 Hungarian algorithm (HA)

The Hungarian algorithm is a modified form of the primal-dual algorithm that is used to solve network flows. In assignment problems, the Hungarian algorithm changes the weights in a matrix to locate the optimal assignment. Eventually, a new matrix is obtained in which the optimal assignment is identified [67].

El-Anwar and Chen [68] proposed a modified Hungarian algorithm to solve post-disaster temporary housing problems. They considered the problem as an integer problem. An earthquake simulation example was used to examine the model's efficiency. The number of decision variables was determined by multiplying the housing alternatives (178) with the number displaced families (5000). Throughout the 13 temporary housing problems, a varying number of decision variables were considered. In terms of the running time, the Hungarian algorithm has shown superiority over integer programming. In the example, the running time for integer programming increased exponentially as the number of decision variables increased, and ran out of memory in case more than 24,000 decision variables were used. The Hungarian algorithm, on the other hand, solved all the problems with the maximum number of decision variables (890,000).

3.14 Mixed-integer nonlinear programming (MINLP)

MINLP is an optimization problem in which the variables are constrained to continuous (e.g., costs, dimensions, mass, etc.) and integer values (typically binary 0 and 1), and the solution space and the objective functions are represented by nonlinear functions [69–71]. To solve complex problems that involve nonlinearity and mixed-integers, MINLP utilizes the combination of mixed-integer programming (MIP) and nonlinear programming (NLP) [72]. Thus, in solving MINLP problems, the approach is not considered a direct problem solver. The methods used to solve MINLP optimization problems include: branch and bound method, benders decomposition, and outer approximation algorithm [73].

- Fan and Xia [74] used MINLP to reduce energy consumption in residential buildings. The objectives of the study were to increase the energy savings and

economic benefits within budget limitations. The example of a 69-year old house was used to test the model, in which the retrofitting plan included the insulation materials for the roof and external walls, windows, and the installation of solar panels. The model proved to be effective in minimizing the energy consumed by the building; from the results obtained, in a 10-year period, the house could save around 288.44 MWh.

- Karmellos et al. [75] also used MINLP to optimize the energy used by a building. The minimization of energy consumption every year and the cost of investments were the two main objectives in the optimization process. To test the model's soundness, the energy consumption in two houses was investigated. The first case involved a new house located in the UK while the second case was an existing house located in Greece. Fifty-four decision variables were accounted for in the model, which represented different building components including electrical appliances, building envelope, and lighting and energy systems. The model was effective in solving the optimization problem of and building energy. It was found that energy consumption goes down when investments in energy efficiency are increased.

3.15 Hybrid approaches

One way in approaching complex optimization problems is to combine two or more techniques together in order to overcome the deficiencies that one or some of them may possess. This approach could affect the overall quality of the solution in an optimization problem. The hybridization of methods has shown its efficacy in accomplishing optimization quality in construction. Hybrid methods have different operational characteristics in tackling optimization problems. While some hybrid methods work by carrying the entire solution process as a single novel technique, others work in tandem whereby one method works on some steps of the solution process and the other steps are completed by another method.

NSGA-II was hybridized with other approaches to solve optimization problems in construction planning, scheduling, energy conservation, transportation, and environmental design. For example:

- Mungle et al. [76] used fuzzy clustering-based genetic algorithm (FCGA) to find optimal solutions for the trade-off problem of time, cost and quality within the construction tasks. The method hybridized the fuzzy clustering approach with NSGA-II. In addition, AHP was utilized to measure the construction activities' quality. To evaluate the model's efficiency, a highway construction project was selected as an example. The authors used the example in three cases with different number of activities, i.e., eighteen, twelve, and seven-activity networks, in which the proposed approach was compared to other methods. The results of the comparison showed that FCGA surpassed MOPSO, MOGA and SPEA-II in terms of diversity as well as the speed and degree of convergence.

- Monghasemi et al. [77] proposed an approach that combines NSGA-II with MOGA to solve a discrete problem of cost, time, and quality in construction project scheduling. An 18-activity highway construction project was used to examine the proposed model. MOGA was utilized to search the large size of 3.6 billion solutions and obtain near true optimal solutions. Shannon's entropy method was used to assign normalized weights to the three objectives in the obtained solutions. These weights were used to rank the solutions by

performing the evidential reasoning method, which assist decision makers in assessing each solution in terms of performance.

- Brownlee and Wright [78] proposed modified approaches of NSGA-II on a simulation-based optimization problem for building energy. The minimization of energy usage and construction cost were the two objectives in the optimization process. The aim of the study was to find an approach that surpasses the basic NSGA-II in terms of convergence rate and solution quality. The study used a middle floor from a commercial office building in three different cities to test the proposed model. The authors merged NSGA-II with two other approaches, namely radial basis function networks and deterministic infeasibility sorting. These approaches enabled the model to prevent the elimination of infeasible solutions and to keep them in the population. The objectives were represented by 50 decision variables (30 continuous, 8 integers and 12 categorical) and 18 inequality constraints. Moreover, the optimization runs were limited to 5000 completed within almost a day by six parallel simulations. The model was found superior to the basic NSGA-II in two of the three building examples.

- Xu et al. [79] proposed a multi-objective bi-level PSO (MOBLPSO) to optimize the minimum cost network flow of construction material transportation in terms of duration and cost. In the upper level of the model, the time to transport materials in addition to direct costs were minimized by the contractor by selecting the most convenient routes for transporting materials. Depending on the decisions made in the model's upper level, every transporter's flow of material in those routes were considered by the transportation manager to reduce the costs of transportation. Because of the complexity of the problem the PSO approach was hybridized with two other methods, one in each level. In the upper level, PSO was integrated with Pareto Archived Evolution Strategy (PAES) to keep the best position for the solutions up to date. In the lower level, PSO used passive congregation to prevent the convergence from happening too early. The case of an actual hydropower construction project was utilized to examine the model's soundness. The model outperformed multi-objective bi-level genetic algorithms (MOBLGA) and the multi-objective bi-level simulated annealing algorithm (MOBLSA).

- Xu et al. [80] conducted a similar study to the one mentioned above, but in this study the cost and duration of transportation were considered as fuzzy random variables. A fuzzy random simulation-based constraint checking procedure was coupled with MOBLPSO to solve the transportation assignment problem which was used to control the flow of materials within a given period. The road network of an existing hydropower project was used for the evaluation of the model. With accounting for uncertainties, the model showed its efficiency and capability of solving the transportation problem.

- Zhang et al. [81] proposed immune genetic PSO (IGPSO) which couples immune genetic algorithm with PSO. The approach was used to tackle the trade-off problem of time-cost-quality in construction, and accounting for bonus and penalty. The hybrid method in the research obtained its characteristics from three methods: (1) from the immune algorithm, whereby the hybrid method inherits the immune selection and the memory recognition; (2) from the genetic algorithm, which implements mutation and crossover; and (3) by limiting the particles' maximum velocity using the constriction

factor in PSO, which speeds up the convergence in initial steps. In addition, the study used a PERT network instead of CPM for the schedule. The model was applied on the 19 activities of a three-floor office building, and proved its effectiveness in solving the trade-off problem.

- In the trade-off problem, some researchers used the double-loop technique, in which the internal loop executes the simulation, while the external loop carries out the optimization process. However, this technique uses MCS and can sometimes take days to finish the process. Therefore, Yang et al. [82] proposed a procedure that combines the double-loop into one, and used MCS and support vector regression (SVR) with PSO to expedite the process of obtaining optimal solutions for the time-cost trade-off problem. MCS was set to assess the initial solutions' objective values, and a decision function gained by SVR promptly assesses the solutions obtained by PSO for their objective values. SVR's direct assessment contributed in shortening the search time of MCS. To test the model, an 18-activity project was utilized as an example. The results obtained showed that the proposed method was superior compared to the methods that used the double loop.

- Futrell et al. [83] used PSO coupled with Hooke Jeeves and the generic optimization program (GenOpt) to optimize the performance of daylighting and thermal systems in buildings. Hooke Jeeves was utilized to fine-tune the best solution found in the PSO algorithm by locally searching it. The case study of a classroom design was utilized to evaluate the proposed approach. The classroom was tested on windows facing north, south, west, and east. It was found that there was no significant conflict between the optimization objectives when the windows were facing south, west, or east, but there was a significant conflict between those objectives in the case of windows facing north.

- Yahya and Saka [84] used multi-objective artificial bee colony (ABC) with the Levy flights algorithm to find the ideal layout for a construction site. Levy flight which uses a random walk pattern searches food locations found by ABC to locate new solutions. The objective functions of the study were the reduction of the facilities' total handling cost, and minimization of environmental and safety risks. Two practical study cases were used to assess the proposed model. The first case was a residential project consisting of four high-rise buildings, and the second case was a three-floor private hospital. The first case which was a dynamic site layout was taken from Ning et al.'s [85] study, in which they applied a modified ACO. From the results, the model succeeded in optimizing the site layout problems. By comparison, the method proposed by Yahya and Saka [84] surpassed the plain-ABC and the modified ACO used by Ning et al. [85].

- Tran et al. [86] tackled the trade-off problem of time, cost, and quality using the combination of multi-objective ABC with DE. DE was included to use its crossover mutation operators to optimize the stages of exploration and exploitation. A study case of a construction project consisting of 60 activities was used to test the model. The result proved the model's efficacy in the trade-off problem. The approach was also compared against four other approaches that were used to solve the trade-off problem. The proposed method outperformed multi-objective ABC, multi-objective DE, multi-objective PSO, and NSGA-II.

- Marzouk et al. [87] presented a hybrid approach that combined ACO with system dynamics to optimize the selection of sustainable materials. The aim of the study was the maximization of LEED credits and the minimization of cost. The authors employed a study case of a two-floor residential building to validate the efficacy of the model. From the achieved results, the model proved its capability in accomplishing the two objectives of the problem.

- In building maintenance planning, Wang and Xia [88] used a predictive control model and DE algorithm to achieve the optimal retrofitting plan that lowers energy consumption. The study's first objective aimed at increasing a project's internal rate of return. The study's second objective was to increase energy savings while accounting for the sustainability period. The authors tackled the optimization of the maintenance plan in two instances. They started by solving the optimization problem without the assumption of uncertainties. They then solved the problem with uncertainties, in which the predictive control model was utilized. To check the approach's validity, a case study that involved the retrofitting of an office building consisting of 50 stories was considered. The results showed that the proposed approach was effective in finding the optimal maintenance plan.

The complexity of the problems in construction projects makes objective optimization usually difficult using a single approach. Hybrid techniques are effective and useful in generating optimal solutions in complex optimization problems. In some studies, these hybrid methods have outperformed some methods in their basic and variant forms. In scheduling for example, they were superior to multi-objective PSO, multi-objective ABC, multi-objective DE, MOGA, SPEA-II, and NSGA-II. In material logistics, they surpassed multi-objective bi-level GA and multi-objective bi-level SA. In site planning, they outperformed the basic form of ABC and one of the ACO variants. Finally, in sustainability, they were superior to NSGA-II.

4. Conclusion

This review included 55 papers that were published in refereed journals and conference proceedings published in the years 2012–2016. The authors of these papers conducted studies using various multi-objective optimization methods in the construction industry. There were 16 methods used in these studies in which some of the authors justify their picks on multiple factors (e.g., construction project type, project size, number of objectives, number of constraints, convergence rate, problem complexity such as constraints' nonlinearity with discontinuity and continuity, etc.). Moreover, some methods were found to be more efficient than others in some studies. For example, in water network planning, Creaco et al. [30] showed that their NSGA-II using a probabilistic approach was superior to NSGA-II used by Creaco et al. [29] in an earlier study in which they used a deterministic approach. The GA proposed by Aziz et al. [6] in a scheduling problem outperformed the GA utilized by Feng et al. [7] for the same case study. Fallah-Mehdipour et al. [26] concluded that NSGA-II has performed better than multi-objective PSO in solving a scheduling problem. Most of the time, it is difficult to guarantee the performance of a method until it is compared with another method.

The most common number of objectives used in the literature is two and three. As expected, cost and duration were the most targeted objectives as cost and duration are important objectives for all construction practitioners. The quality objective has also drawn the interest of researchers as they sometimes include it in

trade-off problems with cost and/or duration. However, quality has not been optimized in any other set of objectives than three-objective optimization problems. The energy and environment category is an important candidate in the optimization process, as it came after cost and duration objectives based on the number of times it was optimized. That may be the result of efforts to optimally construct sustainable buildings and lower the depletion of natural resources.

Among the multi-objective methods used in the literature, NSGA-II was the most used method. NSGA-II has proven its capability in solving optimization problems in different fields of construction. In addition to its popularity among researchers, NSGA-II has many advantages that make it suitable for many types of optimization problems such as obtaining diverse solutions in Pareto-front, low computational complexity, solving problems that involve nonlinearity and discontinuity.

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