A qualitative framework for selection of optimization algorithm for multi-objective trade-off problem in construction projects

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Abstract

Purpose – The purpose of this paper is to develop a qualitative framework for the selection of the most appropriate optimization algorithm for the multi-objective trade-off problem (MOTP) in construction projects based on the predefined performance parameters.

Design/methodology/approach – A total of 6 optimization algorithms and 13 performance parameters were identified through literature review. The experts were asked to indicate their preferences between each pair of optimization algorithms and performance parameters. A multi-criteria decision-making tool, namely, consistent fuzzy preference relation was applied to analyze the responses of the experts. The results from the analysis were applied to evaluate their relative weights which were used to provide a ranking to the algorithms.

Findings – This study provided a qualitative framework which can be used to identify the most appropriate optimization algorithm for the MOTP beforehand. The outcome suggested that non-dominated sorting genetic algorithm (NSGA) was the most appropriate algorithm whereas linear programming was found to be the least appropriate for MOTPs.

Originality/value – The devised framework may provide a useful insight for the construction practitioners to choose an effective optimization algorithm tool for preparing an efficient project schedule aiming toward the desired optimal improvement in achieving the various objectives. Identification of the absolute best optimization algorithm is very difficult to attain due to various problems such as the inherent complexities and intricacies of the algorithm and different class of problems. However, the devised framework offers a primary insight into the selection of the most appropriate alternative among the available algorithms.

Keywords Optimization, Scheduling, Construction project, Questionnaire survey

Paper type Research paper

Introduction

In the present scenario of the construction industry, the demand for simultaneous fulfillment of many objectives such as maximization of quality, profit, safety, etc., and minimization of time, cost, resources, risk, environmental impact, etc., is increasing due to varied interests of the related stakeholders (Kandil *et al.*, 2009). Because of this, such a problem is becoming a multi-objective optimization (MOO) problem for the project planning, scheduling and monitoring team (Zhou *et al.*, 2013). Many researchers have tried to optimize two to three objectives simultaneously (Tavana *et al.*, 2014; Zheng, 2017). Several results have been derived pertaining to various specific problems by the application of available MOO algorithms.

There are many multi-objective trade-off models developed based on different optimization algorithms (Tavana *et al.*, 2014; Maghsoudlou *et al.*, 2016) to solve a multi-objective trade-off problem (MOTP). These optimization algorithms can be broadly classified as mathematical, heuristic and meta-heuristic (Deb *et al.*, 2002). Usually, the mathematical algorithm provides a deterministic solution to the problem. On the other hand, heuristic and meta-heuristic algorithms provide stochastic solutions (Zhou *et al.*, 2013). Thus, optimization approaches can be divided into two streams: deterministic and stochastic. The deterministic approach takes benefit of the analytical dimensions of the problem to generate a series of points that converge

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to a global optimum. The stochastic approach works on the probabilistic translation rules applicable in a given scenario to eliminate infeasible solutions and hence found to be more efficient and flexible than the deterministic approach. However, obtained results will not necessarily be a global optimum (Yang, 2010) as it is well known that no algorithm can be apt for all. This study incorporates optimization algorithms belonging to each of the three categories, namely, mathematical, heuristic and meta-heuristic.

There are many studies in which the solutions obtained by the application of various algorithms on the specific problem are compared to identify the appropriate algorithm (Deb and Jain, 2014; Abadi *et al.*, 2016; Zoraghi *et al.*, 2017). Also, various performance parameters have been devised by several researchers which can help in the identification of the aptest algorithm for the problem (Deb and Jain, 2014; Maltese *et al.*, 2016; Bezerra *et al.*, 2017). Moreover, in some studies, even the solutions obtained from the application of algorithms presented a confounding scenario, which could not be cleared even with the help of performance parameters (Maghsoudlou *et al.*, 2016). Instead, MCDM methods had to be used to decide for the suitable algorithm (Maghsoudlou *et al.*, 2016). However, these processes of identification of the algorithm on the basis of comparison of results are time consuming and cumbersome. There is a dearth of frameworks which can suggest the optimization algorithm which will be the most suitable for solving a specific problem involving multi-objectives. Thus, there is a need to develop a qualitative framework which can utilize the predefined performance parameters to identify the aptest algorithm for a specific problem.

In this study, the authors have attempted to develop a qualitative framework for the selection of optimization algorithm for MOTPs. The selection process chosen was based on the preference relationship as established by the optimization experts who participated in the study. Simon (1957) clarifies a more practical behavior of the person's preference at the time of choosing one alternative over the other which is fuzzy in nature. To take this into account, the selection framework developed in the study is based on consistent fuzzy preference relation (CFPR) method rather than the other methods such as analytical hierarchy preference (AHP) and the technique for an order of preference by similarity to ideal solution (TOPSIS).

This paper consists of six sections. The first section provides a brief introduction to the study. The second section presents the related literature review. The third section explains the research method and various steps involved in the application of CFPR. The results and discussions of this paper are presented in the fourth and fifth sections, respectively. The concluding remarks are provided in the last section of the study.

Literature review

In the past 25 years, optimizing construction project schedule has grasped a significant amount of attention (Zhou *et al.*, 2013; Zheng, 2017). Day by day, the interest of construction practitioners is expanding toward fulfilling more objectives simultaneously in a construction project. It has given rise to the development of algorithms to deal with the explicit problem of optimization in construction. Among various available algorithms, the selection of an efficient optimization algorithm for optimal construction project scheduling is a difficult exercise for project schedulers because it is not the area of their expertise.

The optimization algorithms used for MOTPs in construction mainly includes integer/linear programming (IP/LP), genetic algorithm (GA), non-dominated sorting genetic algorithm (NSGA), ant colony optimization (ACO), particle swarm optimization (PSO) and so on (Zhang and Xing, 2010; Ozcan-Deniz *et al.*, 2011). Previous optimization models considered only a single parameter (Lu and Li, 2003) of the construction project (such as time, cost, resource, quality, etc.) as the objective function. Subsequently, two-objectives (Koo *et al.*, 2015) and then multi-objectives (Afshar and Dolabi, 2014) were considered in a construction project.

There are many optimization algorithms available for solving MOTPs. In order to select the appropriate algorithm for any specific problem, many performance parameters are available in the literature (Jiang *et al.*, 2014; Maltese *et al.*, 2016; Bezerra *et al.*, 2017). With the help of the performance parameters a researcher may be able to assess the performance of an algorithm (Coello and Lamont, 2004). The performance parameters mentioned in literature are the number of decision variables, the convergence order of the algorithm, coverage, diversity, global performance measure, local performance measure, computational complexity and so on (Deb and Jain, 2014; Bezerra *et al.*, 2017).

In the decision-making process, setting appropriate selection criteria is the most important (Ibadov, 2015). Nicoară (2007) considered various performance measures for comparing optimization algorithms. It was observed that for the MOO problem, optimization algorithm did not provide the exact solution; rather, they provided an approximate solution for the problem. The researcher compared three GAs for a bi-objective problem with respect to diversification of population and other performance parameters. Deb and Jain (2014) also emphasized on the diversity of the population and suggested that inclusion of a well-diversified function can enhance the performance of the MOO algorithm. The researchers compared the NSGA II and NSGA III, where NSGA III maintains the well-spread reference point and continuously upgrades the diversity of the population.

Lili and Wenhua (2008) reviewed and compared the various performance measures required for the quantitative assessment of MOO evolutionary algorithms leading to the introduction of two new metrics based on convergence and diversity. Beyer and Deb (2001) investigated the convergence order of real coded evolutionary algorithm and evolutionary strategies. The researchers suggested that global convergence is essential for tracing the optimum solution and reducing the running time of the algorithm. Although the diversity of solution may be ascertained to be the focus of the optimization algorithm practitioners, there are other performance parameters which are essential for the selection of an apt optimization algorithm. Out of that, one of the performance parameter can be the number of decision variables (Andersson *et al.*, 2016) which contributes toward the complexity and difficulty of an optimization problem (Weise *et al.*, 2012; Maltese *et al.*, 2016). As the complexity increases in the optimization problem due to numerous decision variables, the effectiveness of the optimization algorithm suffers.

The experimental information available on MOO is extensive (Beyer *et al.*, 2002), but the precise selection of algorithms specific to a problem is challenging (Muñoz *et al.*, 2015). Since past decade, a number of optimization algorithms have been developed and it became extremely difficult for the professionals to get familiar to all those optimization algorithms (Muñoz *et al.*, 2015). Selection of an algorithm needs a comprehensive knowledge regarding all the aspects of optimization algorithm, through a critical literature and the expert knowledge (Blum *et al.*, 2011). With the help of literature review and expert's knowledge, a framework can be developed which will help in selection of optimization algorithm and to understand and assess the performance.

In order to decide the most suitable algorithm for a specific problem, there are several studies (Abadi *et al.*, 2016; Zoraghi *et al.*, 2017) in which the algorithms are applied on the problem and then the results are compared to identify the best one. There are many studies (Nicoară, 2007; Lili and Wenhua, 2008; Deb and Jain, 2014; Maghsoudlou *et al.*, 2016; Bezerra *et al.*, 2017) which provide the performance parameters to compare the effectiveness of the optimization algorithm.

Also, there are some studies in which the application of these performance parameters provides a perplexing situation which makes it difficult to decide on the best algorithm. For example, Maghsoudlou *et al.* (2016) proposed a MOO model and obtained the solution for MOTP. However, due to the lack of benchmark available in the literature to validate the solutions, the researchers applied two other popular algorithms to solve the problem. Furthermore, the solutions obtained were compared on the basis of four metrics. Different algorithms were found to perform better with respect to the different metrics. This offered a confounding situation to the researchers as they were unable to decide the best algorithm despite having all the solutions available. Finally, the researchers had to use AHP–TOPSIS method to select the algorithm with the best performance in terms of all the metrics simultaneously.

However, these processes of selecting the appropriate algorithm after the application of various algorithms on the problem are cumbersome. Hardly there is any framework available that can suggest the most appropriate optimization algorithm beforehand by the application of predefined performance parameters from the literature. This reinforces the need for a qualitative framework for selecting the best algorithm for a specific problem beforehand so as to avoid the cumbersome processes of applying various algorithms. This becomes the trigger for the authors to conduct this study. This type of qualitative framework may provide the decision makers with a faster and reliable way to select the best algorithm to solve the problem.

From the literature review of various studies, different kinds of optimization algorithms pertaining to the various categories of deterministic, heuristic and meta-heuristic were explored. The literature provides the various performance parameters based on which an optimization algorithm can be compared. But in the literature, comparative prioritization of the performance parameters has not been discussed. Also, the necessity of the consideration of many performance parameters simultaneously has been established through various studies. The authors have tried through the current study to bridge the gap in previous studies.

Research methodology

The innate/inherent complexities and intricacies in the MOTP are not predefined. Also, it changes continuously as per the nature of the objectives (resource optimization/cost optimization/safety optimization, etc.). To deal with this uncertain and fuzzy behavior, this study applies the CFPR for the selection of the optimization algorithm for MOTPs in construction.

In CFPR, a pairwise comparison matrix is constructed by using additive transitivity (Wang and Chen, 2007) unlike multiplicative preference relation (MPR) based methods such as AHP. The AHP requires $n(n-1)/2$ comparison matrices whereas the CFPR requires only $(n-1)$ matrices (Chen and Chao, 2012). Due to its additive transitivity property and requirement of only $(n-1)$ matrices (Herrera-Viedma *et al.*, 2004), the CFPR method becomes advantageous and effective in the decision-making process over the AHP. The CFPR ensures that comparatively lesser time and effort is invested by the decision makers (Chen and Chao, 2012). The method rationally provides the priority in decision-making problems (Wang and Chen, 2007). Many researchers had been using the CFPR method for selection/prioritization/ranking in the various fields effectively (Wang and Chen, 2007; Chen and Chao, 2012; Ibadov, 2015). All these advantages corroborate the soundness of CFPR and its applicability for this study.

The methodology adopted for the study is shown in Figure 1. The various steps involved in the ranking of the optimization algorithms are identification of performance parameters and optimization algorithms, data collection using questionnaire survey and analysis through CFPR. These are discussed below.

Step 1: identification of performance parameters and optimization algorithms

Identification of performance parameters

The performance of an optimization algorithm depends on several parameters. From the literature, 13 performance parameters are identified, namely, accuracy, computational complexity, consistency associated with the localization of all the optima, convergence order of the algorithm, coverage, diversity (distribution spread), dominated volume of solutions

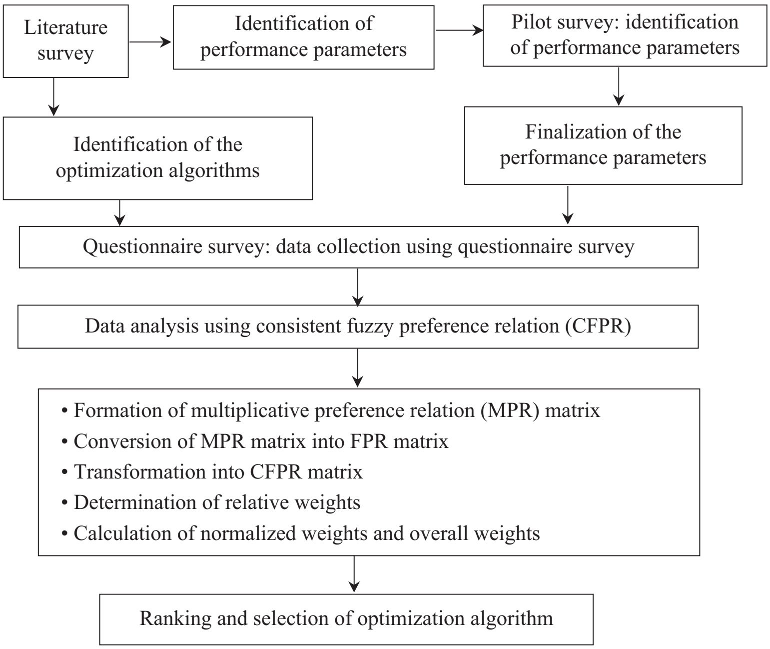

Figure 1. Methodology for ranking of optimization algorithms

with respect to the reference sets, expected number of evaluation for success, generational distance measure, global performance measure, local performance measure, programming complexity and number of decision variables. Table I shows the summary of identified performance parameters along with their brief description and references.

Finalization of performance parameters

The 13 parameters were finalized by conducting a pilot study where the experts were asked to add/remove/modify the performance parameters listed in Table I. The questionnaire for the pilot survey was sent to ten experts for evaluation. Out of ten, only five experts responded. The average experience of the respondents was 20.6 years. However, during the pilot survey, the identified performance parameters remained unchanged. Thus, the 13 parameters ascertained from the literature review were validated.

Identification of the optimization algorithms

Many optimization algorithms are available in the literature (Afshar *et al.*, 2009; Koo *et al.*, 2015; Zheng and Zhong, 2017) to solve different classes of optimization problems of construction industry. Study of a total of 60 plus research papers (see Table II) was undertaken to check the optimization algorithms used in trade-off problems. There are three classes of algorithms, namely, deterministic, heuristic and meta-heuristic (Deb, 2001). The optimization problem is divided into different categories based on the number of objectives: single-objective, bi-objective, multi-objective and many objectives. Figure 2 summarizes the popularity of different class of optimization algorithms according to the number of references found in the selected papers. Within the three classes of optimization – deterministic, heuristic and meta-heuristic – the application of meta-heuristic approach is maximum (63.33 percent) in MOO problem followed by deterministic (23.33 percent) and heuristic (13.33 percent).

S. No.	Performance parameters	Brief description	References
1	Accuracy	This indicates closeness of generated non-dominated solutions from the best-known solution available for the test case undertaken	Nicoară (2007)
2	Computational complexity	This indicates the extent of computational demand in an algorithm	Marler and Arora (2004), Deb and Jain (2014)
3	Consistency associated with the localization of all the optima	This considers the consistency in finding all the points of optimal solution on running the algorithm time and again	Nicoară (2007)
4	Convergence order of the algorithm	This depicts the closeness toward optimal solution (a front is said to converge if all its solutions are Pareto-optimal)	Beyer *et al.* (2002), Nicoară (2007), Lili and Wenhua (2008), Deb and Jain (2014), Maltese *et al.* (2016), Hutahaean *et al.* (2016), Bezerra *et al.* (2017)
5	Coverage	Coverage illustrates how many different non-dominated solutions are generated and how well are they distributed?	Nicoară (2007), Lili and Wenhua (2008), Deb and Jain (2014), Jiang *et al.* (2014), Maghsoudlou *et al.* (2016), Bezerra *et al.* (2017)
6	Diversity	Diversity refers to the extent of the front, and more specifically, to the distance between the extreme solutions of a front	Deb *et al.* (2002), Nicoară (2007), Lili and Wenhua (2008), Deb and Jain (2014), Jiang *et al.* (2014), Maltese *et al.* (2016), Hutahaean *et al.* (2016), Maghsoudlou *et al.* (2016), Bezerra *et al.* (2017)
7	Dominated volume of solutions with respect to the non-dominated sets	This indicates crowding of good solution vs bad solution	Jiang *et al.* (2014)
8	Expected number of evaluation for success	This depicts how fast algorithm converges toward optimal solution	Nicoară (2007)
9	Generational distance measure	This shows how far the known Pareto front is from true Pareto front?	Lili and Wenhua (2008), Maghsoudlou *et al.* (2016)
10	Global performance measure	This is used to evaluate the algorithm's behavior in the long term	Beyer *et al.* (2002), Nicoară (2007)
11	Local performance measure	Local performance measure evaluates the algorithm power to improve the population (of solutions) state from one generation to the next generation	Beyer *et al.* (2002), Nicoară (2007), Lili and Wenhua (2008), Maltese *et al.* (2016)
12	Programming complexity	Programming complexity refers to the intricacies involved in the process of programming an algorithm	Marler and Arora (2004)
13	The number of decision variables	The number of decision variables decides the complexity of the process involved in the formation of optimization objective	Weise *et al.* (2012), Andersson *et al.* (2016), Ma *et al.* (2016), Maltese *et al.* (2016)

Table I.
Identified performance parameters

As evident from Figure 2, the critical path method (CPM) has been chosen in only 5 percent of the total number of references used, which justifies its rare applicability toward MOO problems. The hybrid algorithm was also excluded from the study as it combines the characteristic of different basic algorithms which makes it difficult to explain which performance parameter is dominated by the other in the optimization process. After omitting CPM and hybrid algorithm, six prominent algorithms were selected for this study, namely, IP/LP, heuristic methods (HM), GA, PSO, ACO and NSGA. A brief introduction of these algorithms is given in the Appendix.

Class of algorithm	Algorithm	Single-objective	Bi-objective	Multi-objective
Deterministic	CPM	Tamimi and Diekmann (1988), Waugh and Froese (1991), Lu and Li (2003)	Kallantzis and Lambropoulos (2004)	
	IP/LP	Mattila and Abraham (1998), Gomar *et al.* (2002), Palacio and Larrea (2017)	Liu *et al.* (1995), Burns *et al.* (1996), Huang and Halpin (2000), Elazouni and Gab-Allah (2004), Ipsilandis (2007)	Khang and Myint (1999), Tareghian and Taheri (2006)
Heuristic	HM	Prager (1963), Hegazy *et al.* (2000), Zhang *et al.* (2006c), Elazouni (2009), Wongwai and Malaikrisanachalee (2011)	Fondahl (1962), Siemens (1971), Moselhi and El-Rayes (1993)	
Meta-heuristic	GA	Chan *et al.* (1996), Kim and Ellis (2008), Kadri and Boctor (2018)	Li and Love (1997), Feng *et al.* (1997), Hegazy (1999a, b), Leu and Yang (1999), Zheng *et al.* (2004), Zheng and Ng (2005), Eshtehardian *et al.* (2008), Long and Ohsato (2009), Koo *et al.* (2015)	Sriprasert and Dawood (2003), Senouci and Eldin (2004), El-Rayes and Kandil (2005), Afshar and Dolabi (2014)
	PSO	Zhang *et al.* (2006a, b)	Aminbakhsh and Sonmez (2016)	Zhang and Xing (2010), Maghsoudlou *et al.* (2016)
	ACO		Ng and Zhang (2008), Afshar *et al.* (2009)	Afshar *et al.* (2007), Lakshminarayanan *et al.* (2010)
	NSGA		Fathi and Afshar (2010), Ghoddousi *et al.* (2017)	Ozcan-Deniz *et al.* (2011), Ghoddousi *et al.* (2013), Tavana *et al.* (2014), Monghasemi *et al.* (2015), Maghsoudlou *et al.* (2016), Abadi *et al.* (2016)
	Hybrid	Guo *et al.* (2010), (GA +PSO)	Li *et al.* (1999), (GA +Machine learning), Rahimi and Iranmanesh (2008), (GA+PSO), Chen and Shahandashti (2009) (GA+simulated annealing), Zoraghi *et al.* (2017), (PSO-GA, GA-GA, SA-GA)	Ashuri and Tavakolan (2011), (GA+PSO), Zheng and Zhong (2017) (hybrid GA), Zheng (2017) (weighted sum and GA)

Table II. Optimization algorithms used for trade-off problems

Step 2: data collection using questionnaire surveys

As seen from Figure 1, the study started with the identification of 13 performance parameters and 6 prominent optimization algorithms from the literature. A questionnaire was prepared based on the identified performance parameters and optimization algorithms. The questionnaire used the nine-point scale as suggested by Saaty (1977). To test the language and understanding of the questionnaire, a pilot survey was performed and necessary modifications were done (Tripathi and Jha, 2018). The questionnaire was floated through Google form and electronic mail to the optimization practitioners from different academic organizations as well as industry. The respondents were asked to compare the optimization algorithms with respect to each identified performance parameter.

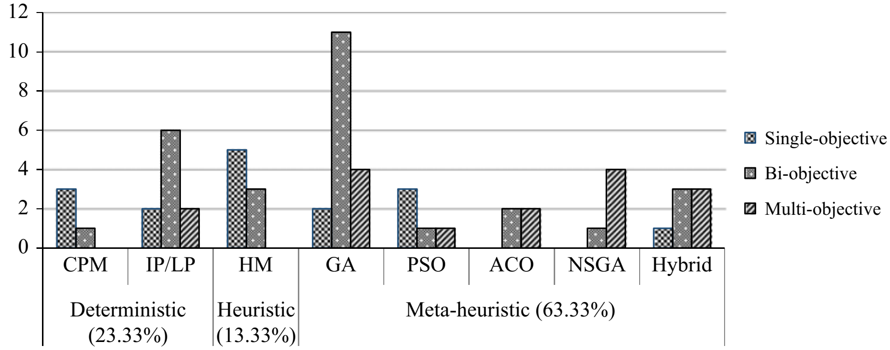

Figure 2.
Optimization algorithms in solving different classes of optimization problems

For better results of this study, it was essential to select appropriately a group of knowledgeable respondents engaged in the continuous research and development of newer optimization algorithms. Hence, the various optimization experts were identified from the web pages of the different prestigious institutions of India and reputed journals pertaining to this study. Initially, more than 100 experts were identified from different areas of optimization. The finalization of the selection of experts was carried out on the basis of the following:

- the experts should have been involved directly in the relevant research;
- the experts should have participated actively in the optimization field; and
- the experts should have an experience on the six algorithms considered in this study.

Based upon the aforementioned criteria, 45 experts were finally shortlisted for this study. Out of those 45, the authors were able to garner responses from 16 experts. The small sample size of 16 was not felt a major issue as it is considered as an accepted practice in the AHP application. There are many instances of AHP application in the literature where a relatively smaller sample size has been used. For example, Wu *et al.* (2010) carried out their study relying on the 8 responses for analyzing 5 marketing criteria to select an optimal marketing strategy. Similarly, Wang and Lin (2009) used 12 responses to choose the most appropriate managerial strategy by considering 6 criteria. Azimi *et al.* (2011) on the other hand used 12 responses employing 14 criteria in order to prioritize the strategies in Iranian mining sector. Cheng *et al.* (2017) considered 13 criteria to select the most appropriate research and development project by collecting 18 responses. Salman *et al.* (2007) conducted a study to assess the viability of a build-operate-transfer project employing only 8 responses.

The average experience of the 16 respondents in our study is about 11–12 years. Hence, the responses presented by the experts might be deemed reliable. The profiles of experts are shown in Table III. Out of these 16 experts, 14 were academicians (12 were professors, 1 was project associate and 1 was research scholar) while remaining 2 were industry practitioners.

Table III.
Respondents' profile

Characteristics	Category	Number of respondents	%
Respondents' experience (years)	< 5	3	19
	5–9	5	31
	10–19	4	25
	⩾20	4	25
Respondents' profile	Academician	14	87.5
	Industry practitioner	2	12.5

Most of the experts were academicians as they practice regularly in the related areas of research, development and application of the optimization algorithm and are continuously updated. The lesser participation of the industry experts was because they did not deal with the optimization algorithm directly in the scheduling, but instead used the software such as Microsoft Project, Primavera, PTB training simulator, etc. Out of the 16 responses, 12 were collected from the Google form and remaining 4 were collected through the electronic mail.

The questionnaire consisted of three parts. Part 1 consisted of personal details of the respondent, part 2 consisted of comparative questions on performance parameters and part 3 contained comparative questions on algorithms. The respondents were asked to express their preference of one performance parameter over another on the basis of importance. Then each algorithm was compared with respect to another on the basis of their individual characteristics with respect to the performance parameters in the third part of the questionnaire.

To check the consistency within the scores and reliability of responses, Cronbach's α and Spearman's rank correlation coefficient were calculated. The value of Cronbach's α was recorded as 0.765 for the responses given by the experts which justifies the reliability of the responses. To check the consistency between the response of the academicians and industry practitioners, Spearman's correlation coefficient (R) has been calculated. The value of R was found to be 0.720 at an allowable significance level of 0.05. So, it may be concluded that the level of consistency between respondents is statistically significant and reliable for conducting this study. In other words, there is no difference between the opinions of two sets of respondence, namely, academicians and practitioners.

Step 3: data analysis using consistent fuzzy preference relationship

The responses obtained were analyzed by CFPR which normally include the following steps:

(1) formation of MPR matrix;

(2) conversion of MPR into fuzzy preference relation (FPR) matrix;

(3) transformation into CFPR matrix;

(4) determination of the relative weights of the performance parameters and algorithms;

(5) determination of the normalized weights; and

(6) overall weights of optimization algorithms.

CFPR is much easier to implement as it requires only (n−1) comparisons if the number of factors is n. Apart from the lesser number of comparison, it also does not require consistency check as required in the case of AHP.

Formation of MPR matrix

Herrera-Viedma *et al.* (2004) proposed a CFPR matrix described as a set of alternatives, $A = \{a_1, a_2, \ldots, a_n\}$, associated with a reciprocal MPR $R = (a_{ij})$ for $a_{ij} \in [1/9, 9]$. The a_{ij} was obtained by the geometric mean of all the responses collected by the questionnaire survey using the following equation:

$$a_{ij} = \left(\prod_{i=1}^{n} \left(a_{ij}\right)_m \right)^{\left(\frac{1}{m}\right)}, \tag{1}$$

where m is the number of the respondents, $(a_{ij})_m$ is the preference of i over j given by mth respondent.

A pairwise comparison matrix was prepared with the help of the collected responses. The preferences of the respondents, namely, R_1, R_2, R_3, …, R_{16} for GA over NSGA were 0.125, 0.333, 0.111, …, 0.111, 0.14. From Equation (1), geometric means of all the preferences were calculated. For example, $a_{21} = (0.125 \times 0.333 \times 0.111 \times \ldots 0.111 \times 0.14)^{(1/16)} = 0.97$. Similarly, all the other cell members (a_{23}, a_{34}, a_{45} and a_{56}) of Table IV were calculated.

Similarly, all other MPR matrices were formed for optimization algorithms with respect to each performance parameter. Also, the MPR matrices were formed for each performance parameter separately.

Conversion of MPR matrix into FPR matrix

After generating the MPR matrix, the corresponding FPR matrix, $P = (p_{ij})$ with $p_{ij} \in [0, 1]$ which is calculated by $p_{ij} = 1/2(1+\log_9 a_{ij})$ (Herrera-Viedma *et al.*, 2004). The other members of the matrix are calculated as per the following equations:

For an FPR $P = (p_{ij})$ the following statements are equivalent:

$$p_{ij} + p_{jk} + p_{ki} = 3/2;\ i \leqslant j \leqslant k. \tag{2}$$

From Equation (2), p_{ii} will be:

$$p_{ii} + p_{ii} + p_{ii} = 3/2,$$

so:

$$p_{ii} = 1/2. \tag{3}$$

$$p_{i(i+1)} + p_{(i+1)(i+2)} + \cdots + p_{(j-1)j} + p_{ji} = \frac{(j-i+1)}{2} \forall i \prec j. \tag{4}$$

The FPR matrix is prepared with the help of MPR matrix. The cell elements fall just above the diagonal elements calculated by the equation $p_{ij} = 1/2\ (1+\log_9 a_{ij})$. According to this equation, $p_{12} = (1/2)\ (1+\log_9 a_{12}) = (1/2)\ (1+\log_9 0.97) = 0.49$. Similarly, other cells (p_{23}, p_{34}, p_{45} and p_{56}) have also been calculated.

The other members of the matrix were calculated with the help of Equation (4). For example, the element p_{21} was calculated as $p_{21} = (2-1+1)/2 - p_{12} = 1 - 0.49 = 0.51$. Similarly, remaining cell members were calculated in FPR matrix.

FPR matrix for the optimization algorithm with respect to the performance parameter –"computational complexity" is shown in Table V.

Similarly, all other FPR matrices were formed for the optimization algorithms with respect to each performance parameter. Also, the FPR matrices were formed for each performance parameter separately.

Table IV. MPR matrix of optimization algorithms w.r.t. performance parameter "computational complexity"

Computational complexity	GA	NSGA	ACO	PSO	HM	IP/LP
GA	1.00	0.97				
NSGA		1.00	0.94			
ACO			1.00	0.64		
PSO				1.00	2.21	
HM					1.00	1.22
IP/LP						1.00

Transformation of FPR matrix to CFPR matrix

In most of the cases, all the elements of FPR matrix fall in the interval [0, 1], but in few cases, some of the elements of FPR matrix fall in the interval $[-k, 1+k]$, $k > 0$. To revise the value from $[-k, 1+k] \rightarrow [0, 1]$, matrix is transformed by the transformation function shown in Equation (5) (Chen and Chao, 2012). That transformed matrix (p') retains the reciprocity and additive consistency within the matrix. The transformation matrix p' is called CFPR matrix. In Table VI, CFPR matrix is shown after applying the transformation function:

$$p_{ij}' = \frac{(p_{ij}+k)}{(1+2k)}, \tag{5}$$

where p_{ij} is the element in the FPR matrix falling in the interval $[-k, 1+k]$, and p_{ij}' is the element in the FPR matrix falling in the interval [0, 1].

In Table IV, it can be seen that that $p_{61} = -0.01$ does not lie in between [0, 1] and hence CFPR needs to be applied in the next step. The calculation of the CFPR matrix for the cell p_{21}' is shown below based on Equation (5):

$$p_{21}' = (p_{21}+k)/(1+2 \times k) = (0.51-0.11)/(1-2 \times 0.11) = 0.51.$$

Similarly, the other cell elements of CFPR matrix are calculated.

Similarly, all other CFPR matrices were formed for the optimization algorithms with respect to each performance parameter. Also, the CFPR matrices were formed for each performance parameter separately.

Determination of relative weights

The relative weights of the performance parameters (W_{pp}) and that of the optimization algorithms (W_{oa}) were computed using the following equation (Chen and Chao, 2012):

$$w_i = \frac{\sum_{j=1}^{n} p_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n}(p_{ij})}. \tag{6}$$

For example, row average of GA is (0.50+0.49+0.48+0.40+0.55+0.58)/(6) $= 0.5$. Similarly, the row averages of the other optimization algorithms are calculated.

Computational complexity	GA	NSGA	ACO	PSO	HM	IP/LP
GA	0.50	0.49	0.48	0.38	0.56	0.60
NSGA	0.51	0.50	0.49	0.38	0.56	1.11
ACO	0.52	0.51	0.50	0.40	0.58	0.62
PSO	0.62	0.62	0.60	0.50	0.68	0.73
HM	0.44	0.44	0.42	0.32	0.50	0.55
IP/LP	0.40	−0.11	0.38	0.27	0.45	0.50

Table V. FPR matrix of optimization algorithms w.r.t. performance parameter "computational complexity"

$k = -0.11$	GA	NSGA	ACO	PSO	HM	IP/LP
GA	0.50	0.49	0.48	0.40	0.55	0.58
NSGA	0.51	0.50	0.49	0.40	0.55	1.00
ACO	0.52	0.51	0.50	0.42	0.56	0.60
PSO	0.60	0.60	0.58	0.50	0.65	0.69
HM	0.45	0.45	0.44	0.35	0.50	0.54
IP/LP	0.42	0.00	0.40	0.31	0.46	0.50

Table VI. CFPR matrix of optimization algorithms w.r.t. performance parameter "computational complexity"

The relative weight of GA is (0.50)/(0.50+0.58+0.52+0.60+0.45+0.35) = 0.17. Similarly, the relative weights of other optimization algorithms were calculated. The relative weights for the optimization algorithms with respect to performance parameter "computational complexity" are shown in Table VII.

Similarly, all relative weights are calculated for performance parameters and optimization algorithms.

Determination of normalized weights

The normalized weights of the optimization algorithm (W) were obtained by using the following equation (Patel *et al.*, 2016):

$$W = W_{pp} \times W_{oa}, \tag{7}$$

where W_{pp} is the relative weight of the performance parameter, and W_{oa} is the relative weight of the optimization algorithm.

The third and fifth columns of Table VIII show the relative weights of the performance parameters and the optimization algorithms, respectively. The normalized weights of the optimization algorithms are shown in the last column.

Overall weights of optimization algorithms

The optimization algorithms were ranked as per their overall weights. These weights were calculated as per the arithmetic mean of the normalized weights using the following equation:

$$\text{Overall weight} = \frac{\sum W}{n}. \tag{8}$$

For example, the overall weight of the optimization algorithm GA is computed as follows:

$$\text{Overall weight}_{GA} = \frac{\sum W_{GA}}{13} = \frac{(0.014+0.006+0.013+\cdots+0.013+0.111)}{13} = 0.188.$$

The overall weights of all the algorithms are shown in Table IX. The optimization algorithm NSGA was ranked 1 with the highest weight (0.204). Similarly, GA was ranked 2 with next higher weight (0.188) and so on.

Results

This study was carried out in two parts. The first part was the identification of optimization algorithms and the performance parameters, while the second part was the selection process based on a questionnaire survey using the CFPR method. The weights of the performance parameters and the algorithms were calculated based on the respondent's preference. The final ranking of the algorithms was according to their overall weights.

The final weights of the performance parameters can be seen from Table VII. The top 5 performance parameters were: global performance measure (0.111); the number of decision

Table VII. Relative weights of optimization algorithms w.r.t performance parameter "computational complexity"

Optimization algorithm	Row average ($\sum p_{ij}$)	Relative weight
GA	0.50	0.17
NSGA	0.58	0.19
ACO	0.52	0.17
PSO	0.60	0.20
HM	0.45	0.15
IP/LP	0.35	0.12

S. No.	Performance parameter (PP)	Weights of PP	Weights of optimization algorithm (normalized weights)					
			GA	NSGA	ACO	PSO	HM	IP/LP
1	Accuracy	0.058	0.249 (0.014)	0.205 (0.012)	0.186 (0.011)	0.143 (0.008)	0.106 (0.006)	0.112 (0.006)
2	Computational complexity	0.034	0.167 (0.006)	0.192 (0.006)	0.173 (0.006)	0.201 (0.007)	0.151 (0.005)	0.116 (0.004)
3	Consistency associated with the localization of all the optima	0.073	0.174 (0.0127)	0.192 (0.014)	0.186 (0.0135)	0.159 (0.0116)	0.157 (0.0115)	0.132 (0.0097)
4	Convergence order of the algorithm	0.061	0.167 (0.010)	0.203 (0.012)	0.176 (0.011)	0.171 (0.010)	0.170 (0.010)	0.112 (0.007)
5	Coverage	0.074	0.170 (0.013)	0.209 (0.016)	0.156 (0.012)	0.183 (0.014)	0.160 (0.012)	0.121 (0.009)
6	Diversity	0.060	0.182 (0.011)	0.221 (0.013)	0.170 (0.010)	0.161 (0.010)	0.150 (0.009)	0.118 (0.007)
7	Dominated volume of solutions with respect to the reference sets	0.081	0.183 (0.015)	0.193 (0.016)	0.184 (0.015)	0.147 (0.012)	0.172 (0.014)	0.121 (0.010)
8	Expected number of evaluation for success	0.098	0.219 (0.021)	0.207 (0.020)	0.157 (0.015)	0.153 (0.015)	0.136 (0.013)	0.128 (0.013)
9	Generational distance measure generational distance measure	0.078	0.201 (0.016)	0.198 (0.016)	0.141 (0.011)	0.178 (0.014)	0.161 (0.013)	0.121 (0.009)
10	Global performance measure	0.111	0.184 (0.020)	0.218 (0.024)	0.182 (0.020)	0.169 (0.019)	0.131 (0.014)	0.116 (0.013)
11	Local performance measures	0.083	0.167 (0.014)	0.190 (0.016)	0.175 (0.014)	0.175 (0.014)	0.183 (0.015)	0.109 (0.009)
12	Programming complexity	0.080	0.163 (0.013)	0.191 (0.015)	0.181 (0.014)	0.192 (0.015)	0.149 (0.012)	0.124 (0.010)
13	The number of decision variables	0.109	0.202 (0.022)	0.217 (0.024)	0.198 (0.022)	0.168 (0.018)	0.131 (0.014)	0.083 (0.009)

Table VIII. Normalized weights of optimization algorithms variables (0.109); expected number of evaluation for success (0.098); local performance measures (0.083); and dominated volume of solutions with respect to the reference sets (0.081). It was observed that these five performance parameters alone accounted for almost 50 percent of the total weight based on which a specific optimization algorithm was preferred with respect to others by the respondents.

Every optimization algorithm has its own pros and cons and their specific ability to deal with a problem. In this study, the overall weights of the optimization algorithms calculated on the basis of the identified performance parameters can be seen from Table VIII. The descending order of weights for the algorithms is: NSGA (0.204); GA (0.188); ACO (0.175); PSO (0.168); HM (0.150); and IP/LP (0.116). Based on these weights, the ranks were allotted to the optimization algorithms to solve the MOTPs in construction projects. The rank order suggests that the NSGA is the most desirable algorithm to deal with MOTPs and IP/LP is the least desirable algorithm.

Discussion

The performance parameter, namely, "global performance measure" was found to be the most important parameter based on its highest recorded weight (0.111) while choosing an optimization algorithm. The "diversity" of the solution was the focus of the former optimization algorithm practitioners. However, "global performance measure" may be deemed as one of the major parameters as it was found to be more important in evaluating the algorithm's behavior in the long term (Beyer *et al.*, 2002). Here, the focus is inclined toward the various aspects of computer resources used for the algorithm. Also, the emphasis is laid on the expected running time required for reaching the optimum or its peripheral area in continuous search spaces. Efficiency can be measured by counting the number of function evaluations instead of using the fitness evaluations pertaining to the specific MOO as it is time consuming.

The NSGA was ranked first due to its highest weight (0.204). NSGA, developed by Srinivas and Deb (1994), is used widely to resolve MOO problem. It has various applications both in research and development and in the industry to solve specific problems. For example, it has received significant appreciation for its varied applications in solving trade-off problems for specific objectives (Abbasnia *et al.*, 2008; Zahraie and Tavakolan, 2009; Ghoddousi *et al.*, 2013). The fitness assignment feature of NSGA makes it advantageous over the other algorithms. This feature considers the non-dominance property of solution. Typically, diverse and reasonably good spread solution is obtained using a sharing function parameter in accordance with the application of the non-dominance property of the algorithm (Goldberg and Richardson, 1987). However, an NSGA solution remains sensitive to the values of the sharing function.

The updated version of NSGA such as NSGA II (Deb *et al.*, 2002) and NSGA III (Deb and Jain, 2014) has been put forward to enhance its performance. NSGA III has been developed specifically to deal with many objective problems. A MOO problem becomes many objective problems when the objective functions are more than three. Diversity is one of the main

Table IX. Final weights of optimization algorithms

Optimization algorithm	Arithmetic mean	Ranking
GA	0.188	2
NSGA	0.204	1
ACO	0.175	3
PSO	0.168	4
HM	0.150	5
IP/LP	0.116	6

goals of any MOO algorithm. It refers to finding a set of solutions which are diverse enough to represent the entire range of the Pareto-optimal front. NSGA II used crowding distance to maintain the diversity. But in the case of many objectives, diversity cannot be maintained by the distance calculation as it becomes computationally expansive (Deb and Jain, 2014). However, by the use of a set of uniformly distributed reference points, NSGA III gives rise to the diversity of the solution in many objectives problem.

This algorithm has been extensively used to solve multi-objective construction management problems. Some of them are minimization of project duration (Gomar *et al.*, 2002), time-cost trade-off (Abbasnia *et al.*, 2008), time-cost-resource (Zahraie and Tavakolan, 2009; Ghoddousi *et al.*, 2013; Ma *et al.*, 2016), time-cost-environment impact (Ozcan-Deniz *et al.*, 2011), time-cost-pollution (Marzouk *et al.*, 2008), etc. Due to its well-diversified solution and ease of implementation, NSGA is widely used.

The selection of an algorithm is sensitive with respect to the performance parameters. The results obtained by different algorithms vary with respect to various performance parameters as different algorithms are designed to solve specific problems. On the one hand, an optimization algorithm may perform very well with respect to a specific performance parameter whereas it may be deemed inefficient with respect to another. Maghsoudlou *et al.* (2016) analyzed the three algorithms, namely, multi-objective invasive weeds optimization algorithm (MOIWO), NSGA II and multi-objective PSO based on four matrices/performance parameters, namely, mean ideal distance (MID), spacing metric (SM), diversification metric (DM) and spread of non-dominance solution (SNS). The finding showed that MOIWO performed better in case of DM, the NSGAII in SNS and PSO in MID. In the case of SM, the results obtained through PSO and NSGA II were found to be competitive. The PSO and NSGAII performed well with respect to two matrices while MOIWO performed well with respect to only one matrix. From the findings till this stage, it was not clear as to which algorithm may be deemed better overall. Hence, the researchers have done an AHP–TOPSIS analysis and re-evaluated each of the algorithm based on the above-mentioned performance parameters and found out that MOIWO outperformed PSO and NSGAII. The results strongly suggest that the selection of an optimization algorithm depends on the performance parameter based on which an algorithm is selected. In this study, the authors have selected the algorithm based on 13 performance parameters and found out that NSGA II outperforms other algorithms.

Conclusion

The selection of an appropriate MOO algorithm has been challenging. It is often difficult to get the holistic viewpoint of different algorithms for a specific problem and decide the best fit amongst them. To sort out this problem, the authors have tried to develop a qualitative framework which chooses an optimization algorithm based on the performance parameters involving experts' opinions. The analysis of the selection process is carried out by the CFPR method. A total of 13 performance parameters and 6 alternative optimization algorithms were considered during the analysis. A total of 16 experts participated in the survey, who expressed their respective preferences for the identified algorithms based on the performance parameters. With the help of CFPR, the overall weights of the optimization algorithms were calculated and the algorithms were ranked accordingly. NSGA was ranked first due to its highest recorded weight followed by GA, ACO, PSO, HM and IP/LP. The final ranking depicts a way for choosing the best alternative among the identified optimization algorithms. Although it is nearly impossible to choose the best optimization algorithm due to various reasons such as the different class of problems, complexities in the development of the algorithm, etc., the present qualitative selection framework provides a primary insight into choosing the best alternative among the available algorithms based on their performance parameters. The study is limited to the MOTPs to construction projects. It has only considered those algorithms for the selection process which were identified as being the most widely used according to the literature review. Also, the newly developed hybrid algorithm was not considered due to the difficulty in the assessment of a particular performance parameter as it is derived basically from the combination of different algorithms. Incorporation of the hybrid algorithm in a similar exercise may lead to alteration in the results which may, in turn, open new avenues for further research. Although a construction project involves many stakeholders and each one of them have different interests in the project, the bottom line is invariably governed by the success of the project in terms of time, investment and quality, and a fair return to the stakeholders. Thus, if the concept discussed in the paper for the selection of an apt algorithm is implemented, there is very likelihood that even the policy makers will be inclined to use it for updating and fine tuning future legislation governing construction and other industries. The framework definitely will also assist in solving the problems related to smart grid, networking, traveling salesman, etc., by way of identifying an apt optimization algorithm in advance. Moreover, it will reduce the computational effort and help researchers realize reduction in overall resources consumed in dealing with the optimization process and is likely to attract wider adoption.

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Appendix

The six algorithms mentioned in the paper are briefly described below:

(1) Integer/Linear programming (IP/LP): IP/LP is a deterministic approach and is based on the linear relationship of objective function and constraints. The formulation of objective function and constraints usually simplifies a practical problem so that it will fit in the IP/LP model. Because the knowledge of the construction project planner is generally limited to the mathematical formulation, the formulation process of the objective function can be time consuming and prone to errors. This method provides an exact and accurate result. However, the linear relationship of the objectives and constraints which is being used in their formulation is a major limitation of this method.

(2) Heuristic methods (HM): the HM relies on the experience and the rule of thumb of the decision makers for solving problems. In this method, a non-computer approach is involved which requires less computational effort as compared to IP/LP. HM is simple and has widely been used in construction scheduling problem. It is developed based on the individual problems which cannot be generalized for all. These methods optimize single-objective problem very efficiently but are marred by difficulties while dealing with multi-objective problems. This is one of the limitations of the HM which restricts its application in multi-objective problems. In HM, global optima are not guaranteed as it provides a single solution rather than a set of solutions from which a decision maker can choose a suitable solution in accordance with the respective construction scenario.

(3) Genetic algorithm (GA): in the 1960s, Holland proposed a GA to search solutions for both constrained and unconstrained optimization problems based on the mechanics of natural selection and natural genetics. GA consists of three main operators, namely, selection, crossover and mutation. However, when applied in a MOO, it is basically focused on the selection operator

as it is used for sorting the GA population whereas the other two operators are mostly the same across different kinds of MOO problem. The algorithm can be trapped in local optima if the selection operator is not efficient in finding the fitness value of the function. Moreover, it does not guarantee the global optima for the problem but it always gives a better solution compared with the other solution. GA is a population-based approach. The population is one of the crucial parameters, which can affect the computational time, as well as the optimization output of the algorithm. A larger population may lead the algorithm to an excessive computational effort whereas a lesser population may trap the algorithm to the local optima, which may prevent it to converge to global optima. Also, it is difficult to set the stopping criteria for the GA and the uncertain construction environment further restricts its effectiveness.

(4) Ant colony optimization (ACO): ACO was developed by Dorigo and his colleague in 1996 based on the ability of the ants to find the food from the nest through the shortest path. Initially, it was used to solve the traveling salesman problem. An ant colony is a virtuous tool for solving the optimization problem and provides a good solution at a faster rate. However, further study is required to understand the applications and limitations of the ACO.

(5) Particle swarm optimization (PSO): PSO was developed by Kennedy and Eberhart in 1995. It is inspired by a herd of migrating birds, which reaches an unknown destination by their social-psychological behavior. The PSO calculation is very simple and has no mutation calculation, which results in faster completion. However, global and local optima are not guaranteed in the process. Moreover, it is not suitable for the scattered and non-coordinated system such as the energy field.

(6) Non-dominated sorting genetic algorithm (NSGA): NSGA was developed by Srinivas and Deb in 1994 based on the Pareto front. The major difference between NSGA and GA is the selection process. NSGA uses non-dominating sorting and crowding distance phenomena for fitness evolution in the generation of the new population whereas the GA uses the normal selection operators such as roulette wheel and tournament selection. To deal more effectively in multi-objective problems, Deb *et al.* (2002) and Deb and Jain (2014) proposed a second and third version of the algorithm. The latest version (NSGA III) maintained the population diversity by providing well-spread reference points, which could automatically be updated for the next generation. The model has been applied from 3-objective to 15-objective test optimization problems. Also, it has been applied for 3-objective and 9-objective real-life optimization problems separately. In all these problems, NSGA III algorithm performed successfully and resulted in a well-converged as well as a well-diversified set of optimal points.

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