APPLICATION OF MULTIPLE CRITERIA DECISION MAKING METHODS IN CONSTRUCTION: A SYSTEMATIC LITERATURE REVIEW

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Abstract. Decision making is a key to business or project success in any sectors, especially in construction that requires handling numerous information and knowledge. Multiple criteria decision making (MCDM) is an important tool for decision problem solving due to simultaneous consideration of multiple criteria and objectives. Various MCDM methods are continually emerging and tend to be increasingly adopted to address the real-world construction problems. Therefore, it is urged to systematically review the existing body of literature to demonstrate the evolution of the mainstream MCDM methods in general and their application status in construction. A total of 530 construction articles published from 2000 to 2019 are selected in this study and then categorized into seven major application areas using a novel systematic literature review (SLR) methodology. The bibliometric analysis is then used to describe the research trend. Subsequently, the qualitative discussion by themes is conducted to analyze the application of MCDM methods in construction. A further discussion makes it possible to identify the potential challenges (e.g. applicability, robustness, postpone effect, dynamic and prospective challenges and scale problem) to existing research. It also contributes to the recommendation of future directions for the development of MCDM methods that would benefit construction research and practice.

Keywords: decision support system, construction, multiple criteria decision making, multiple attribute decision making, multiple objective decision making, systematic literature review.

Introduction

The significant role of construction in economic development has been widely acknowledged and long recognized (Giang & Pheng, 2011; Zhao et al., 2012). Construction activities can often be described as a summary of various tasks and requirements, involving conflicting aspects and factors to consider (Jato-Espino et al., 2014). Due to the sophistication of technologies and the increase in complexity and dynamics, decision making in construction projects is becoming complicated and difficult (de Azevedo et al., 2013; Bakht & El-Diraby, 2015). Therefore, accurate and agile decisions should be made in a scientific manner based on qualitative or quantitative analysis (Zavadskas et al., 2016a), rather than relying solely on intuition or experience. Otherwise, there may be a latent negative effect on resource utilization, cost efficiency, environment and sustainability (Sitorus et al., 2019).

Based on theoretical and practical requirements, a wide variety of MCDM methods have been developed in general (Zavadskas et al., 2016b), with even minor variations or a combination of existing methods to create new branches of relevant research (Velasquez & Hester, 2013). This may favor decision makers in providing more choices, but appear to be a paradoxical result, as selecting an appropriate method among various alternatives may be difficult, particularly for decision makers with a limited understanding of MCDM methods. As an operational research method comprehensively considering computational and mathematical tools in a certain environment to find a suitable solution (Zavadskas et al., 2014), MCDM has attracted considerable academic attention across a number of industry sectors. Due to the complex and dynamic nature, the above-mentioned problem is particularly true for the use of MCDM methods in the construction industry and its projects. Therefore, this paper addresses the problem through a thorough investigation of existing MCDM methods and a systematic synthesis of their application in construction.

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Actually, several previous attempts have been made to review the literature on the use of MCDM methods in construction. For example, Jato-Espinó et al. (2014) evaluated the application of six MCDM methods and their hybrid variants in construction. Sierra et al. (2018) reviewed the state-of-the-art of 19 multiple-criteria assessment methods for social sustainability in infrastructure development. Despite that, some limitations exist within these previous literature reviews. Firstly, only a limited number of MCDM methods are discussed, ignoring the differences and connections among various MCDM methods. Secondly, the majority of these literature reviews are not strictly conducted in a systematic manner, yielding results that are supposedly affected by bias. Thirdly, some literature reviews are based on different MCDM methods instead of their application areas, which tend to be method-oriented rather than problem-oriented.

This research aims to systematically review the application status of MCDM methods in the construction industry. The specific objectives of this research are: (1) to classify MCDM methods in general and analyze their relationships; (2) to identify the evolution of MCDM methods; (3) to design a novel methodology for systematically reviewing the utilization of MCDM models in construction from the bibliometric perspective; (4) to determine the main areas of applying MCDM models in construction; and (5) to analyze the potential gaps and provide future directions for MCDM research in construction. The following sections are arranged accordingly to achieve the research objectives one by one.

1. Overview of MCDM methods

1.1. Concept and general structure of MCDM

Although MCDM methods are widely diverse, how to evaluate a set of alternatives in terms of a number of criteria is a key issue of MCDM methods in general (Triantaphyllou, 2000). MCDM refers to making decisions in the presence of multiple, usually conflicting criteria (Zavadskas et al., 2014). It can be perceived as a process of evaluating the real-world situations based on various qualitative and/or quantitative criteria in certain circumstances to find a suitable alternative/solution. Roy (1996) defined four types of problems that MCDM can solve: (1) selection problem, in which MCDM is adopted to choose a specific alternative or develop a selection procedure; (2) sorting problem, in which MCDM is used to assign the alternatives in terms of norms or build the assignment procedure; (3) ranking problem, in which MCDM is applied to order the alternatives according to the preference or set up the ranking procedure; and (4) description problem, in which MCDM is utilized to present the alternatives and their consequences. The problem structure of MCDM is treated as a combination of problems and methods (Keeney, 1982; Cinelli et al., 2014). From this perspective, the whole MCDM process can be divided into four stages, namely: problem structuring, problem formulating, method selection and evaluation, and decision recommendation (Bouyssou et al., 2006; Tsoukiás, 2007; Bigaret et al., 2017).

1.2. Classification of MCDM

MCDM consists of many subfields. Existing studies show that MCDM can mainly be divided into multiple attribute decision making (MADM) and multiple objective decision making (MODM) (Hwang & Yoon, 1981; Chen & Hwang, 1992; Zavadskas et al., 2014; Kahraman & Otay, 2019). According to Hwang and Masud (1979), the distinctive feature of MADM is that there are usually a limited number of predetermined alternatives. The selection of alternatives is based on inter- and intra-attribute comparisons, which involve explicit or implicit trade-offs. On the contrary, the alternatives of MODM are not predetermined. MODM methods are designed to find the alternatives in terms of their constraints to attain the acceptable levels of objectives. Triantaphyllou (2000) concluded that MADM concentrates on discrete decision spaces, whereas MODM studies decision problems whose space is continuous.

1.3. Evolutionary development of MADM

The historical origin of MADM can be traced back to the research on utility theory published by Bernoulli in 1738. According to Bernoulli (1738), a decision is made on the basis of the utility value rather than the expected value. von Neumann and Morgenstern (1947) further paved the way for the development of MADM by applying the dynamic mathematic model for strategic interaction between rational decision makers. Nowadays, MADM methods are generally grouped into six categories, including multiple attribute utility (value) functions, pairwise comparisons methods, distance (ratio) to reference point methods, outranking-based MADM methods, fuzzy set methods and their variants, and other MADM methods. Based on Liou and Tseng (2012) and Tseng and Shen (2017), this research summarizes the evolutionary development of MADM methods in the form of dendrogram (see Figure 1). The six categories of MADM are discussed below one by one.

1.3.1. Multiple attribute utility (value) functions

The goal of multiple attribute utility (value) functions is to construct the expression that represents the preference of decision makers based on utility/value functions. Although utility/value functions can be utilized to transform the values of diverse criteria for alternatives, either factual (objective, quantitative) or judgmental (subjective, qualitative), into a common and dimensionless scale (Fülöp, 2001), an obvious drawback of utility/value functions is that the criteria should follow the assumption of independence, which is termed preferential independence. As a result, Choquet (1954) and Sugeno (1974) proposed Choquet integral and Sugeno integral, respectively, to address the interrelationship among the criteria (Angilella et al., 2004). Representative methods in this category include simple additive weighting (SAW) (value added not utility) by MacCrimmon (1968) and multi-attribute utility theory (MAUT) by Keeney and Raiffa (1972) and
Figure 1. Evolutionary development of MADM methods
Keeney and Raiffa (1976). In addition to MAUT, Edwards (1971) developed simple multi-attribute utility rating technique (SMART) for multi-attribute utility measurement. SMART was further corrected by Edwards and Barron (1994) and renamed to SMART using swings (SMARTS). SMART and SMARTS are two simplest MAUT methods (Chen et al., 2010).

The weights of the criteria play a critical role in the methods of this category and have an influence on the process of evaluation. Several studies have been conducted for weights calculation. Keuken et al. (2010) suggested a new step-wise weight assessment ratio analysis (SWARA) technique for the determination of attributes' weights and provided an opportunity to estimate the differences of their significances. Ginevičius (2011) offered factor relationship (FARE) to measure the weights based on the relationships between all the criteria describing the phenomenon considered. Krylov et al. (2014) proposed the Kemeny median indicator ranks accordance (KEMIRA) method to determine criteria priority and select criteria weights in the case of two separate groups of criteria. To address the impreciseness of criteria measurement, Jessop (2014) presented imprecise multi-attribute evaluation (IMP) to describe the weights by a suitable probability distribution. Zavadskas and Podvezko (2016) supported integrated determination of objective criteria weights (IDOCRiW) that combines the weights yielded by the entropy and the criterion impact LOSs (CILOS) method. These weighting methods can also be adopted in the following MCDM methods that involve the weights of criteria.

### 1.3.2. Pairwise comparisons methods

Analytic hierarchy process (AHP) was designed by Saaty (1972), streamlining a complex problem into a hierarchy structure and eliciting the preference by converting the subjective comparison of relative importance into the overall scores or weights. Due to the limitation of independence assumption of criteria for AHP, its extension method analytic network process (ANP) includes the interrelationships among criteria (Saaty, 1996). A wide criticism received is that AHP and ANP over-rely on the subjective opinions of experts or decision makers. Dynamic AHP (DAHP) developed by Saaty (1992) can solve the inconsistency of expert opinions to some extent. Moreover, the impreciseness of expert opinions should be considered. To reduce the comparison data in AHP and ANP, Rezaei (2015) proposed the best-worst method (BWM) to derive the weights based on a pairwise comparison of the best and the worst criteria/alternatives with other criteria/alternatives. The result reveals that BWM is more easily used and performs better compared to AHP and ANP.

### 1.3.3. Distance (ratio) to reference point methods

Distance to reference point methods include technique for order preference by similarity to an ideal solution (TOPSIS) (Hwang & Yoon, 1981), complex proportional assessment (COPRAS) (Zavadskas et al., 1994), multi-attributed border approximation area comparison (MABAC) (Bana e Costa & Vansnick, 1994), Vlsekrterijumska optimizacija i kompromisno resenje (VIKOR) (Opricovic, 1998), multi-objective optimization by ratio analysis (MOORA) (Brauers & Zavadskas, 2006), MOORA plus full multiplicative form (MULTIMOORA) (Brauers & Zavadskas, 2010), additive ratio assessment (ARAS) (Zavadskas & Turskis, 2010), and evaluation based on distance from average solution (EDAS) (Keshavarz Ghorabaee et al., 2015). All these methods are based on the aggregation function that represents the degree of proximity with the reference point to determine the preference. In this process, normalization is adopted to eliminate the units and scale of criteria, and the weights of the criteria can be generated by different methods, such as the weighting methods mentioned in Sections 1.3.1 and 1.3.2.

The best (compromise) alternative of TOPSIS should have the shortest distance from the positive ideal point and the longest distance from the negative ideal point. MABAC ranks the alternatives according to the distance to the border approximation area. As for VIKOR, the best alternative provides a maximum utility of the majority and a minimum of an individual regret. EDAS chooses the best alternative relating to the distance from average solution. COPRAS determines the ranking of alternatives by the calculated utility ratio based on the minimization index and the maximization index. MOORA ranks the alternatives based on the distance with the ratio, which is representative for all alternatives concerning that objective. MULTIMOORA further orders the utility function of alternatives according to the ratio of the product of maximizing attributes values to the product of minimizing attributes’ values. And ARAS ranks the alternatives based on the utility degree calculated by comparison with the ideally best optimality function.

### 1.3.4. Outranking-based MADM methods

Unlike MCDM methods that assume the existence of a single optimal alternative, outranking-based MADM methods follow the principle that one alternative may have a degree of dominance over another (Kangas et al., 2001). As a member in this category, elimination et coix traduisant la realite (ELECTRE) is a family that provides a series of methods (Roy, 1968). ELECTRE I (Roy, 1971) is designed for the selection problem. ELECTRE II (Roy, 1976), ELECTRE III (Roy, 1977) and ELECTRE IV (Roy & Vincke, 1981) characterize the ranking problem by ordering alternatives from the best to the worst. ELECTRE TRI (Yu, 1992), ELECTRE TRI-C (Almeida-Dias et al., 2010) and ELECTRE TRI-NC (Almeida-Dias et al., 2012) tackle the sorting problem by assigning alternatives to predefined sets (Govindan & Jepsen, 2016).

Preference ranking organization method for enrichment evaluation (PROMETHEE) is another family member in this category, which deals with “the appraisal and the selection of a set of options on the basis of several criteria, with the objective of identifying the pros and
cons of the alternatives and obtaining a ranking among them” (Cascales et al., 2015). Brans (1982) developed PROMETHEE I for partial ranking and PROMETHEE II for complete ranking. Soon thereafter, PROMETHEE III and PROMETHEE IV were proposed for interval order and continuous case, respectively. Two extension methods were PROMETHEE V involving the segmentation constraints (Brans & Mareschal, 1992) and PROMETHEE-VI for dealing with the sorting problem and PROMETHEE-CLUSTER for addressing the nominal classification. Similar to PROMETHEE methods, Xu (2001) introduced superiority and inferiority ranking (SIR) method that is based on the utilization of superiority and inferiority values to determine the type of the preference function.

1.3.5. Fuzzy set methods and their variants

For the purpose of dealing with uncertain information, Zadeh (1965) and Bellman and Zadeh (1970) put forward fuzzy set theory (generally Type-1 fuzzy set), which is characterized by a membership function that represents the degree of truth in fuzzy logic. It was generalized by Zadeh (1975) through proposing Type-2 fuzzy set that incorporates uncertainty into the membership function of a fuzzy set. As a special case of Type-2 fuzzy set, interval-valued fuzzy set (IVFS) proposed by Zadeh (1975) and other researchers has attracted great attention because the membership function of interval arithmetic is much simpler than the general Type-2 fuzzy set. Atanassov (1986) introduced intuitionistic fuzzy set (IFS) characterized by the membership degree and non-membership degree, based on which Atanassov and Gargov (1989) further defined interval-valued intuitionistic fuzzy set (IVIFS). In order to express the opinions of decision makers more realistically and accurately, Cuong (2014) proposed picture fuzzy set (PFS), including positive, neutral, negative, and refusal membership functions. As an extension of IFS, Kutlu Gündoğdu and Kahraman (2019, 2020) introduced Spherical fuzzy set (SFS) to raise the membership functions from two to three dimensions.

Sometimes, it is difficult to determine the accurate membership degree of evaluation information. For this reason, Torra and Narukawa (2009) introduced hesitant fuzzy set (HFS), in which the membership degrees are represented by several possible crisp numbers. Smarandache (1998) put forward neurocomputational set (NS) to deal with incomplete, indeterminate and inconsistent decision information through truth, falsity and indeterminacy memberships, generalizing fuzzy set theory, IFS and HFS. The corresponding membership functions of such decision information are non-standard subsets of [0, 1]∗. In addition to the above-mentioned fuzzy set methods, rough set and grey set were proposed by Pawlak (1982) and Deng (1982), respectively, to solve problems in different scenarios. Compared to traditional fuzzy set that addresses subjective uncertainty, such as artificial classification and language description, rough set and grey set relate to objective uncertainty, such as missing information and unpredictable process.

Among existing studies on uncertain MADM, Sakawa et al. (1984) used fuzzy MADM methods to solve non-linear programming problems. Hashiyama et al. (1995) explored dynamic MADM methods by fuzzy neural network. In addition, a large number of pioneers are committed to combining fuzzy set with existing MADM methods, including Fuzzy-AHP (van Laarhoven & Pedrycz, 1983), Fuzzy ELECTRE, Fuzzy PROMETHEE (Perny & Roy, 1992), Fuzzy TOPSIS (Triantaphyllou & Lin, 1996), Fuzzy VIKOR (Opricovic & Tzeng, 2002), Fuzzy-ANP (Mikhailov & Singh, 2003), Fuzzy MOORA (Brauers & Zavadskas, 2006), Fuzzy COPRAS (Zavadskas & Antučiūnienė, 2007), fuzzy decision making trial and evaluation laboratory (DEMATEL) (Hsu et al., 2007), Fuzzy ARAS (Turskis & Zavadskas, 2010) and Fuzzy EDAS (Keshavarz Ghorabaee et al., 2016), etc. (see Figure 1).

With regard to rough set and grey set, Pawlak and Slowiński (1994) utilized rough set in the field of MADM. Tzeng and Tansu (1994) conducted multi-criteria evaluation of grey relation models. Greco et al. (2001) presented grey set theory while Greco et al. (2010) further proposed dominance-based rough set (DSRA) for decision making. Other examples of combining grey set with existing MADM methods include Grey AHP (Xu, 1993), Grey TOPSIS (Chen & Tzeng, 2004), COPRAS of alternatives with grey relations (COPRAS-G) (Zavadskas et al., 2008) and ARAS with grey values (ARAS-G) (Turskis et al., 2013).

1.3.6. Other methods

There are many other methods that do not fall in any of the above MADM categories, e.g. DEMATEL developed by Fontela and Gabus (1972, 1976) for the analysis of cause-effect chain components in complex structural models. To better solve complicated problems, some recent research efforts put emphasis on strengthening single methods with complement methods or replacing existing methods with advanced methods for MADM. For example, the ANP-DEMATEL hybrid can be built to develop interdependent and feedback relationships among criteria (Yang et al., 2008; Wu, 2008; Tzeng & Shen, 2017). Modified VIKOR can be used to deal with “the best of a bad bunch” problem (Opricovic & Tzeng, 2007). Moreover, weighted aggregated sum product assessment (WASPAS) that combines weighted sum mode (WSM) and weighted product model (WPM) significantly improve the accuracy of estimation compared to the individual use of each method (Zavadskas et al., 2012a).

1.4. Evolutionary development of MODM

Based on Liou and Tzeng (2012) and Tzeng and Shen (2017), Figure 2 shows the evolutionary development dendrogram of MODM methods. The concept of vector optimization proposed by Kuhn and Tucker (1951) is...
Figure 2. Evolutionary development of MODM methods
generally recognized as the origin of MODM (Tzeng & Shen, 2017). Most real-life MODM problems have several conflicting objectives to be considered simultaneously, which may be nonlinear. Under such circumstances, there is no single solution that optimizes the conflicting objectives, but there exist a number of Pareto-optimal solutions (Koopmans, 1951) or compromise solutions (Yu, 1973). These solutions cannot improve any objectives without deteriorating other objectives. In other words, MODM aims to solve mathematical optimization problems under specified constraints, involving more than one objective to be achieved simultaneously. Its results are a set of Pareto-optimal solutions or a set of trade-offs in satisfying the conflicting objectives.

1.4.1. No-preference methods

MODM can be divided into methods with no-preference, methods with a priori information, methods with a posteriori information, and methods with progressive information (Cohon & Marks, 1975; Hwang & Masud, 1979; Sengupta et al., 2017). When using no-preference methods, the MODM problem is solved to generate some neutral compromise solutions and the preference of decision makers is not considered during the optimization process. Subsequently, decision makers can select or reject the proposed solution. Global criterion method, also known as compromise programming (Yu, 1973; Zeleny, 1973), can be regarded as the most common example in this category, whose idea is to find the closest compromise solution to the ideal objective vector. However, the challenge is that the solution varies with the change of the metrics to measure the closeness. Normalization is also required when the units and/or orders of objective functions are different.

1.4.2. Methods with a priori information

For methods with a priori information (namely a priori methods), decision makers provide the global preference information, such as certain desired goals or pre-ordered objectives. The Pareto-optimal solution (a close solution) is found through the scalarizing function that combines the preference information and the original problem. A priori methods include goal programming (GP) (Charnes et al., 1955), lexicographic ordering (Fishburn, 1974), etc. They deal with both ordinal and cardinal information. With regard to GP methods, decision makers specify the desired aspiration level (maximum or minimum level). GP is then used to minimize the deviations between the achievement of goals and their aspiration levels. For lexicographic ordering methods, decision makers order the objective functions based on their preference. Subsequently, the objectives are optimized until attaining the unique solution. The common weakness of a priori methods is that the preference of decision makers may be too optimistic or pessimistic. It is also hard for decision makers to express their preference without a good understanding of decision making problems.

Although data envelopment analysis (DEA) and MCDM are generally known as two different subfields of operational research and management science, they handle similar problems (Stewart, 1996). Actually, many DEA methods can be derived directly from GP (Liu & Sharp, 1999). DEA is a mathematical programming-based method for performance evaluation where multiple inputs and outputs exist for decision making units (Cook et al., 2014). A large number of DEA methods are based on the CCR model proposed by Charnes et al. (1978). Subsequent to the CCR model, Banker et al. (1984) developed the BCC model to address the variable return to scale. Charnes et al. (1985) further introduced additive models into DEA, which was extended by Charnes et al. (1987). Sengupta (1992a, 1992b) incorporated fuzzy sets into DEA models to deal with the impreciseness or vagueness of inputs and outputs. According to Liu et al. (2016b), cross-efficiency in DEA by Doyle and Green (1994), stochastic DEA by Simar and Wilson (2000), network DEA by Fare et al. (2000), and dynamic DEA by Tone and Tsutsui (2010) represent the major schools of DEA-related research.

Traditional MODM optimization techniques focus on valuation in a fixed and given environment. However, it is usually hard to optimize all the objectives simultaneously. Thus, the trade-offs among the objectives become the key to such algorithms. Actually, the trade-offs are properties of imperfectly designed systems (Zeleny, 2011). For this reason, Zeleny (1982, 1986) proposed de Novo programming to enhance traditional mathematical programming by relaxing the assumption of fixed resources. As a result, the optimization trade-offs are eliminated. Among follow-up studies on de Novo programming, Li and Lee (1990) proposed a model of de Novo programming with fuzzy coefficients. Sasaki et al. (1995) implemented genetic algorithm (GA) for de Novo programming with fuzzy goals and constraints, which was based on multiple criteria and multiple constraints (MC2) by Seiford and Yu (1979) and fuzzy MC2 by Shi and Liu (1993). Chen and Hsieh (2006) further built a fuzzy multi-stage method of de Novo programming with the dynamic nature. Huang and Tzeng (2014) extended de Novo programming to changeable space (parameters), helping decision makers to achieve the desired outcomes (aspiration levels) rather than the traditional ideal points.

1.4.3. Methods with a posteriori information

Methods with a posteriori information, also known as “a posteriori” methods, generate the Pareto-optimal solution and present it to decision makers for reference. Such methods deal with a single objective according to the global preference of decision makers. When using the weighting method established by Gass and Saaty (1955) in the category of a posteriori, various weight vectors can be adopted to produce Pareto-optimal solutions. Thereafter, decision makers select a most preferred solution among them. The obvious weakness of this method is that it is only suitable for convex problems and on the other hand weights are not easy to understand. Compared to the weighting method, the ε constraints method proposed by Haimes et al. (1971) can be used for non-convex problems.
It selects one of the objective functions to optimize while converting other objective functions into constraint functions by their bounds. However, there is a concern that the upper bounds are unknown before optimization and therefore have to be set properly to obtain a solution.

Based on GP, Zeleny (1973) developed the method of weighted metrics, finding different Pareto-optimal solutions closest to the ideal objective vector using metrics augmented with various weights. Through this method, decision makers can select the solution according to their preference. The achievement scalarizing function proposed by Wierzbicki (1982, 1986) calculates the weighted distance between the reference point and each Pareto-optimal solution, based on which a new Pareto-optimal solution closest to the reference point is produced. Das and Dennis (1998) developed the normal boundary intersection (NBI) method that is independent of the relative scales of objective functions. The NBI method gives an evenly distributed set of weights to produce a uniformly distributed set of Pareto-optimal solutions, overcoming a lack of even distribution within the above-mentioned methods of weighted metrics. Compared to the NBI method, Messac et al. (2003) further designed the normalized normal constraint method to reduce the possibility of producing dominated solutions.

Evolutionary multi-objective optimization (EMO) is another a posteriori method that optimizes the complex numerical problem based on evolutionary algorithms. EMO represents a problem-independent algorithmic framework that provides a set of guidelines or strategies to explore the solution space more thoroughly and finally obtains a set of solutions that approximate the set of optimal solutions for decision makers’ reference. The origin of evolutionary algorithms in MODM can be traced back to Schaffer (1984) that utilized GA for multi-objective optimization, namely vector-evaluated genetic algorithm (VEGA). Subsequently, Goldberg (1989) revolutionarily designed a new non-dominated sorting procedure, since which different EMO methods have mushroomed. Among these methods, Sakawa et al. (1994) combined fuzzy multi-objective programming by Zimmermann (1978) and EMO to deal with nonlinear goal programming. Michalewicz (1996) pointed out that evolutionary programming methods have a good performance on nonlinear constrained optimization problems.

The current EMO can be generally divided into three categories, namely Pareto based EMO, indicator-based EMO and decomposition based EMO. Pareto based EMO ranks the population of an evolutionary algorithm based on Pareto optimality. Its representative algorithms include SPEA II by Zitzler and Thiele (1999), non-dominated sorting genetic algorithm (NSGA) II by Deb et al. (2002), etc. Since Pareto based EMO does not work well for multiple objectives (e.g. four or more objectives), researchers have started to show interest in the other two families: indicator-based EMO that is guided by an indicator to measure the performance of the set and decomposition based EMO that divides the problem into several subproblems, each of which targets different parts of the Pareto front. The indicator-based evolutionary algorithm (IBEA) (Zitzler & Künzli, 2004) and S metric selection evolutionary multi-objective algorithm (SMS-EMOA) (Emmerich et al., 2005) fall into the category of indicator-based EMO. On the other hand, NSGA III (Deb & Jain, 2014) belongs to the category of decomposition based EMO.

Early EMO approaches do not use an elite-preservation mechanism until the appearance of the second generation of EMO algorithms, such as NSGA II by Deb et al. (2002). Despite that, the second generation of EMO methods does not work well for multiple objectives (e.g. four or more objectives). As a result, the third generation of EMO methods, such as NSGA III by Deb and Jain (2014), is introduced to handle various decision making problems that involve more than four objectives. In recent years, some new EMO methods have been developed, which include particle swarm optimization (PSO), ant colony optimization algorithm (ACO), particle bee algorithm (PBA) and their variants.

### 1.4.4. Methods with progressive information

Methods with progressive information, also known as interactive methods, are generally used to obtain a most satisfactory solution through an iterative process that solves local problems, progressively involving the local preference of decision makers and providing current solutions. Reference point method is a common example of MODM methods in this category, which was proposed by Wierzbicki (1982) based on the achievement scalarizing function. The core idea of this method is directing the search by reference points that represent desirable values for objective functions and generating new alternatives by shifting reference points. The successor methods, such as satisficing trade-off method (STOM) (Nakayama, 1995) and given-unknown-equation-substitute-solve (GUESS) (Buchanan, 1997), share the same idea. Unlike the reference point method by Wierzbicki (1982) that uses reference points, the reference direction approach by Korhonen and Laakso (1984, 1985, 1986) chooses a reference direction, which makes the search process more visual. Based on the nondifferentiable interactive multi-objective bundle-based optimization system (NIMBUS) method by Miettinen (1998), Miettinen and Mäkelä (2006) and Purslane et al. (2014) developed the synchronous NIMBUS algorithm and the interactive EMO method respectively, which have gained comprehensive attention. By comparison, interactive methods are advantageous over non-interactive methods, such as no-preference methods, methods with a priori information and methods with a posteriori information. This is because decision makers usually have enough knowledge about problems but do not necessarily have a deep understanding of theories.
2. Methodology

2.1. Survey methodology

Literature review plays a significant role in conveying the subject knowledge that has been established to readers. It has been improved considerably from traditional narrative review to SLR recently. Unlike traditional narrative review, SLR adopts a rigorous, replicable and transparent review process and meanwhile makes the decisions, procedures and conclusions of reviewers unbiased and traceable (Tranfield et al., 2003; Thomé et al., 2016). For this reason, an enormous application of SLR has been witnessed in different disciplines. The procedure of SLR can be commonly divided into: (1) formulating the question; (2) determining the required characteristics of primary studies; (3) retrieving the sample of potentially relevant literature; (4) selecting the pertinent literature; (5) synthesizing the literature; and (6) reporting the results (Durach et al., 2017).

As mentioned in the Introduction section, there are several existing attempts to review the literature on MCDM methods in construction, such as Jato-Espino et al. (2014) and Sierra et al. (2018). However, few of them are conducted in a systematic manner. Unlike existing literature reviews, this research uses a stepwise method for SLR to assess and aggregate previous research works. It further provides a balanced and objective summary of research evidence for the application of MCDM methods in construction. The detailed steps of searching and filtering can be found in Figure 3. To avoid any bias and random error, this research introduces reliability analysis. During exclusion, coding and classification, nonparametric test is performed to test the reliability of relevant inter-processes.

2.2. Searching methodology

This research mainly focuses on the application of MCDM in construction. Four research questions (see Figure 3) are answered through SLR. Based on the review of the literature on MCDM methods in general (see Section 1), the tendency of MCDM evolution is recognized. Subsequently, 59 keywords, including the mainstream methods mentioned in Sections 1.3 and 1.4, are identified in this research. The strings “decision making” and “construction” are first chosen to narrow the search scope to decision making in construction. Boolean logic “OR” is then used to combine the following string of keywords: “(TS=((decision making OR DM) AND construction AND (MCDM OR MCDA OR MADM OR MODM OR MRDM OR ACO OR AHP OR ANP OR ARAS OR BW OR Choquet Integral OR COPRAS OR DASA OR DE OR DE-MATEL OR De Novo OR EDAS OR ELECTRE OR EMO OR FARE OR Fuzzy Set (theory) OR GA OR Grey Set OR Grey theory OR GUESS OR IBEA OR IDECRW OR IMP OR KEMIRA OR MABAC OR MAUT OR MOORA OR MULTIMOORA OR Multiple criteria OR Nondominated solutions generation method OR Normal boundary intersection methods OR Normal constraint method OR NSGA OR

NIMUS OR PBA OR PROMETHEE OR PSO OR Reference Point Method OR Rough Set OR Rough theory OR SAW OR SMS-EMOA OR SPEA OR SIR OR STOM OR Sugeno Integral OR SWARA OR TOPSIS OR VIKOR OR WASPAS OR Weighting method OR Goal programming))”.

2.3. Selection of data sources and papers

Core collection in Web of Science, a comprehensive scientific citation indexing service provider, is selected as the database for the literature search. Only the articles written in English and cited by Science Citation Index Expanded (SCIE) or Social Science Citation Index (SSCI) are retrieved as the potential literature. The literature search shows very few related articles published before 2000. Therefore, a timespan from 2000 to 2019 was chosen and the baseline sample including 1658 articles in 596 journals was found during the literature search on 30th March 2020. Three exclusion filters are adopted for the baseline sample in order to generate the final literature sample. The first filter excludes the journals that contain less than two articles. As a result, it becomes more possible to ensure the homogeneity of selected articles. The second and third filters eliminate the articles that fall outside the scope of this research through reading titles/abstracts and full contents, respectively.

To ensure the accuracy of literature screening, the whole process is conducted by the first and second authors separately. The individual results of each screening are tested by the related samples McNemar test, a non-parametric test that examines if the statistically significant change exists on a dichotomous trait at two time points for dependent samples. According to the test results, all three pairs pass the test (see Table 1). In other words, no possible bias or error is detected in terms of literature screening. For any different opinions between each filter, joint decision is made after discussion between the first and second authors. Finally, 530 articles from 125 journals are selected as the final literature sample.

2.4. Thematic classification

Content co-occurrence analysis is a systematic and objective means to extract the themes of science and detect the linkages between these themes directly from the subject contents of texts (Sedighi, 2016). Since abstracts are considered as concise descriptions of research contents, this research constructs the distance-based map of terms in titles and abstracts based on content co-occurrence analysis to identify the themes of MCDM application in construction. VOSviewer, a bibliometric mapping software package, is adopted to create the map. A total of 88 terms that occur more than three times are selected from 11841 terms after excluding the term “MCDM methods” and general terms, such as “system” or “method”. Figure 4 shows the results of content co-occurrence analysis, in which nodes represent terms while the distance between two nodes reflects the strength of their linkage. Colors indicate the clusters to which terms are assigned through similarity analysis (van Eck & Waltman, 2010).
## Figure 3. Steps of literature searching and filtering

| Step | Procedure | Content |
|------|------------|---------|
| Step 1 Fumulate research question | Start | RQ1: What is the bibliometric perspective of MCDM in the Construction field?  
RQ2: In which research areas and field applications are MCDM methods applied in Construction?  
RQ3: What are the challenges potentially related?  
RQ4: What are the research tendencies? |
| | Fumulate research question | Inclusion Criteria:  
– Timespan: 2000–2019  
– Language: English  
– Document Types: Peer-reviewed journal article  
– Index: SCI Expanded, SSCI |
| | Fumulate Keyword | Exclusion Criteria:  
– The journal including less than 2 articles  
– The article outside the research scope after reading the title & abstract  
– The article outside the research scope after reading the full contents |
| | Craft inclusion & exclusion criteria | Database: Web of Science  
Searching the keyword  
Deriving the baseline sample: $N = 1658, J = 596$ |
| Step 2 Determine required characteristics of primary studies | Database $N = 1658, J = 596$ |  
Reducing the baseline sample to derive the synthesis sample:  
Exclusion(EXCL) Criteria 1: Remove the journal including solely 1 article;  
Exclusion(EXCL) Criteria 2: Remove the articles that outside the scope of research after reading the title and abstract  
Exclusion(EXCL) Criteria 3: Remove the articles that reading the full articles  
Non-parameter Test:  
Related Samples McNemar test: the null hypothesis is the distributions of different values across two results are equally likely, if the significance is more than the significance level 0.05, then the decision is retain the null hypothesis. |
| | EXCL Criteria 1 | Yes  
McNemar test |
| | EXCL Criteria 2 | No  
McNemar test |
| | EXCL Criteria 3 | Yes  
McNemar test |
| Step 3 Retrieve sample of potentially relevant literature | Database $N = 1658, J = 596$ |  
Content co-occurrence analysis  
Apply coding schemes to extract information  
Wilcoxon test |
| | | Coding the synthesis sample  
Summarizing the findings (methodological aspects of the primary study should be analyzed) and interpretation  
Non-parameter Test:  
Wilcoxon signed ranks test: the null hypothesis is the median of differences between two time points equals 0, if the significance is more than the significance level 0.05, then the decision is retain the null hypothesis. |
| | Content co-occurrence analysis | Yes |
| | Apply coding schemes to extract information |  
Wilcoxon test |
| | | Result and updating the review |
| Step 4 Select pertinent literature | Stop |  
Descriptive analysis of primary studies  
Outlining the knowledge derived from the study synthesis  
Keeping the review updated |
| | | STOP |
As shown in Figure 4, seven major themes for MCDM application in construction are identified, including: (1) contractor (subcontractor) / staff / supplier selection (in red); (2) cost / time / quality performance assessment (in yellow); (3) design / system / method / project / portfolio selection (in blue); (4) layout / location selection (in orange); (5) material / equipment selection (in purple); (6) risk / safety management (in light blue); and (7) sustainability / environment assessment (in green). According to Cobo et al. (2011), sometimes it is hard to determine to which cluster borderline terms belong when using software packages, such as VOSviewer, for bibliometric analysis. In these cases, adjustment by researchers is necessary, taking research questions into consideration. Such adjustment is also included in this research when classifying MCDM application in construction into seven major themes according to the meaning of each term and the essence of each theme.

In order to ensure the objective adjustment and accurate classification, the similar procedure with screening process is conducted to classify the 530 articles into the appropriate themes and subthemes. Obviously, there are continuous observations rather than dichotomies for the themes and subthemes. Therefore, Wilcoxon signed ranks test, a non-parametric test that measures two occasions and assesses the statistically significant differences between two time points, is employed to verify the consistency of the classification results. For the coding theme (frequency for disagree is 18) and subthemes (frequency for disagree is 12), both significances (0.017 and 0.013, respectively) are smaller than 0.05, which reflect that the first and second authors did not elicit a statistically significant difference in the classification results.

### 3. Bibliometric analysis of MCDM methods in construction

#### 3.1. Distribution by publication years

The distribution of 530 articles on MCDM methods in construction by publication years is presented in Figure 5. Despite particular fluctuations, on the whole the number of relevant publications increased from one in 2002 to 140...
in 2019. Different research trends are found for MADM and MODM methods. Since 2005, the number of research papers on MADM methods is usually greater than those on MODM methods, especially in recent years (see Figure 5). Compared to MADM, MODM requires a larger amount of data to achieve a desired level of performance. For this reason, MODM is less utilized and therefore MADM dominates in construction. The number of papers on MADM gradually increased from the minimum in 2005 to the maximum in 2019 although there were slight falls in 2013, 2015 and 2016. On the other hand, the number of papers on MODM methods fluctuated from 2005 to 2019, during which the peak appeared in 2019.

As seen in Figure 6, the number of papers on single methods was greater than the number of hybrid methods from 2005 to 2007. The trend reversed since 2008. As a result, hybrid methods were more commonly observed than single methods from 2008 to 2019. The gap between the two categories increased dramatically in recent four years. Figure 6 shows that the application of hybrid methods in construction rose steadily from 2005 to 2019 with an exception in 2013. On the other hand, the application of single methods fluctuated during the same period with a peak in 2019. As mentioned above, decision making in construction projects is becoming complicated and difficult due to the sophistication of technologies and the increase in complexity and dynamics. The combination of different MCDM methods offsets one’s demerits by another’s merits and therefore better addresses the decision making problem. This explains why hybrid methods become more popular in construction.

Based on the trend analysis, the application of soft computing methods and crisp set methods in construction is presented in Figure 7. It can be seen that both categories have experienced a similar trend regardless of a slight difference. Both of them increased slowly in the initial years from 2000 to 2013 and attracted a significant increase in the last five years. By comparison, the application of crisp set methods is slightly more than that of soft computing methods during the recent 15 years except for 2011–2013 and 2016. With regard to the soft computing methods, the overwhelming majority of publications adopt fuzzy set related methods in comparison with rough set and grey set related methods. This phenomenon can be corroborated from the literature review in Section 1.3, which is due to the continuous development of fuzzy set methods and the popularization of its joint use with other MCDM methods.

3.2. Distribution by journals

After the screening process, 125 journals are left in this research for the literature review. Table 2 presents a list of 21 selected journals that contain at least five papers. Among these journals, Journal of Civil Engineering and Management ranks first, contributing 8.30% of selected articles. It is followed by Journal of Construction Engineering and...
Management (7.74%), Automation in Construction (5.85%), Sustainability (5.47%) and Journal of Management in Engineering (3.40%). Most selected articles are published in construction, engineering or construction/engineering management journals. Some articles are published in sustainability and environment related journals.

3.3. Distribution by authors

Table 3 shows the top eight authors, each of whom has at least five articles on MCDM methods in construction. The number of their articles and the number of their articles’ citations are also presented in Table 3. By comparison, Professor Edmundas Kazimieras Zavadskas from Vilnius Gediminas Technical University is the most authoritative author who has 40 articles on MCDM methods in construction. By the end of March 2020, these articles have been cited for 1547 times.

3.4. Distribution by MCDM methods

As mentioned above, a total of 530 papers are selected for the literature review, based on which it is possible to identify 29 single methods and 94 hybrid methods. The top five most commonly used signal methods are: AHP (60 papers; 11.32%), fuzzy theory (52 papers; 9.81%), GA (24 papers; 4.53%), DEA (16 papers; 3.02%), and ANP (14 papers; 2.64%). Among the hybrid methods used in construction, fuzzy-AHP method (53 papers; 10.00%) ranks first, which is followed by fuzzy-TOPSIS (28 papers; 5.28%), AHP-fuzzy-TOPSIS (8 papers; 1.51%), fuzzy-ANP (8 papers; 1.51%), ANP-DEMATEL (7 papers; 1.32%), and fuzzy-DEMATEL (7 papers; 1.32%). By comparison, hybrid methods that contain fuzzy logic (159 papers; 30.00%) and hybrid methods that contain AHP (104 papers; 19.62%) can be considered as the largest two hybrid groups.

Table 2. Distribution of journals

| No | Journal title                                                | Frequency | Percentage | Cumulative percentage |
|----|--------------------------------------------------------------|-----------|------------|-----------------------|
| 1  | Journal of Civil Engineering and Management                 | 44        | 8.30%      | 8.30%                 |
| 2  | Journal of Construction Engineering and Management          | 41        | 7.74%      | 16.04%                |
| 3  | Automation in Construction                                  | 31        | 5.85%      | 21.89%                |
| 4  | Sustainability                                              | 29        | 5.47%      | 27.36%                |
| 5  | Journal of Management in Engineering                        | 18        | 3.40%      | 30.75%                |
| 6  | Expert Systems with Applications                            | 16        | 3.02%      | 33.77%                |
| 7  | Journal of Cleaner Production                               | 15        | 2.83%      | 36.60%                |
| 8  | Mathematical Problems in Engineering                       | 11        | 2.08%      | 38.68%                |
| 9  | Archives of Civil and Mechanical Engineering               | 10        | 1.89%      | 40.57%                |
| 10 | Journal of Intelligent and Fuzzy Systems                   | 10        | 1.89%      | 42.45%                |
| 11 | KSCE Journal of Civil Engineering                          | 10        | 1.89%      | 44.34%                |
| 12 | Building and Environment                                   | 8         | 1.51%      | 45.85%                |
| 13 | Energy and Buildings                                       | 8         | 1.51%      | 47.36%                |
| 14 | Engineering, Construction and Architectural Management     | 8         | 1.51%      | 48.87%                |
| 15 | International Journal of Project Management                | 8         | 1.51%      | 50.38%                |
| 16 | International Journal of Strategic Property Management     | 8         | 1.51%      | 51.89%                |
| 17 | Symmetry-Basel                                              | 8         | 1.51%      | 53.40%                |
| 18 | Journal of Computing in Civil Engineering                  | 7         | 1.32%      | 54.72%                |
| 19 | Safety Science                                              | 7         | 1.32%      | 56.04%                |
| 20 | Sustainable Cities and Society                              | 7         | 1.32%      | 57.36%                |
| 21 | Technological and Economic Development of Economy           | 7         | 1.32%      | 58.68%                |
| 22 | Others                                                      | –         | 41.32%     | 100.00%               |

Table 3. Publications on MCDM in construction by authors

| No | Author                                      | No. of articles | No. of citations | No | Author                              | No. of articles | No. of citations |
|----|---------------------------------------------|-----------------|------------------|----|-------------------------------------|-----------------|------------------|
| 1  | Edmundas Kazimieras Zavadskas               | 40              | 1547             | 5  | Guiwu Wei                           | 8               | 89               |
| 2  | Zenonas Turskis                             | 25              | 1107             | 6  | Yi-Kai Juan                          | 6               | 165              |
| 3  | Jolanta Tamošaitienė                        | 12              | 657              | 7  | Abdolreza Yazdani-Chamzini           | 6               | 133              |
| 4  | Jurgita Antucheviciene                      | 12              | 250              | 8  | Heng Li                             | 6               | 70               |
As seen in Figure 8, a contour map presents the distribution of single and hybrid methods by publication years. AHP-related methods cover both single AHP and hybrid methods that contain AHP. Similarly, fuzzy-related methods refer to both single fuzzy algorithm and hybrid methods that contain fuzzy algorithm. It is clearly shown in Figure 8 that research using AHP-related and fuzzy-related methods has become more and more intensive in recent ten years. In Figure 8, EMO-related methods mean single and hybrid methods that have relevance to EMO. The contour map in Figure 8 shows slight concentration on research using EMO-related methods during 2010–2011, 2014–2015 and 2017–2019, respectively, although there is no continuous research evidence for the use of EMO-related methods. On the other hand, slight concentration on research on TOPSIS-related methods can be observed during 2011–2012, 2013–2014 and 2016–2019, respectively.

4. Discussion about application themes

4.1. Contractor (subcontractor)/staff/supplier selection (article number = 74)

4.1.1. Bidding

For the potential participants of a project, whether to bid or not bid for the project is one of the most crucial decisions. During the bidding process, a bidder has to find a balance between the expected profit and the chance of winning (Chou et al., 2013). For this purpose, there are generally three solving ideas. The first idea is pair-wising the factors that influence the bid decision to generate their weights and then calculating the bid numbers or comparing the bid alternatives. AHP and improved AHP methods are widely used for this purpose. Fuzzy set (Chou et al., 2013; Plebankiewicz, 2014) and rough set (Shi et al., 2016) can be incorporated into AHP to reflect the human way of thinking and perform the evaluation of linguistic variables. Another idea is developing a benchmark based on expert knowledge and historical information and subsequently providing a ranking of different projects to bid in reference to the benchmark for bid project selection. Fuzzy-TOPSIS (Al-Humaidi, 2016) and DEA methods (El-Mashaleh, 2013; Polat & Bingol, 2017) can be adopted under this circumstance. The last idea is estimating project award prices with the help of artificial intelligence (AI) models, such as artificial neural networks (ANN) and general regression neural network (GRNN) (Shi et al., 2016).

4.1.2. Contractor/subcontractor/supplier selection

Appropriate contractor (subcontractor) and supplier selection is a key to the success of a project (Nieto-Morote & Ruz-Vila, 2012; Abbassianjahromi et al., 2013; Seth et al., 2018). In construction practice, such selection is usually divided into prequalification and bid evaluation (Hasnain et al., 2018). In theory, the client of a project has to select the most competent contractor based on its capability in various aspects. It is the same for the contractor of a project to select its subcontractors and suppliers. How to identify and weight the criteria for measuring the capability of the contractor, subcontractors or suppliers is crucial for right selection. Most MCDM methods can be used to solve this problem. In recent years, some new MCDM methods have been applied to improve the solution. For the identification of selection criteria, single membership is the weakness of traditional fuzzy set methods. Intuitionistic fuzzy values replace single membership values to measure the hesitation margin of decision makers, which make the measurement of uncertainty and fuzziness more flexible (Palha et al., 2016; Wan et al., 2016). Compared to the traditional AHP and/or fuzzy set methods, determining the weights for selection criteria by the hybrid method, such as the combination of DEMATEL, BWM and grey set methods (Yazdani et al., 2019) and the combination of EMO methods (e.g. GA) and fuzzy set methods (Lin et al., 2008), would make the selection model more consistent.
4.1.3. Partner/staff selection
Since project participants play a significant role in project performance, the selection of staff and partners in a project has received considerable academic attention in recent years. Relevant studies can be divided into decision making hierarchy and selection methodology (Shahhosseini & Sebt, 2011). The research on staff selection targets project managers (Zavadskas et al., 2012b; Afshari, 2015, 2017) and key personnel (Shahhosseini & Sebt, 2011). The selection of staff is mainly based on their capability and suitability for the work. On the other hand, the research on partner selection solves the problem from broader aspects, such as the ranking of alternatives (Radziszewska-Zielina, 2010) and the trade-off between minimizing the negative environmental impact and maximizing the positive business performance (Wu & Barnes, 2016). In terms of staff/partner selection, there are relatively more subjective criteria represented by linguistics and vague patterns. Therefore, fuzzy set theory and its related hybrid methods are more efficient under such a circumstance (Shahhosseini & Sebt, 2011). This explains why fuzzy-Delphi method (Afshari, 2015) and fuzzy-AHP (Chen & Wu, 2012) are chosen for the selection of project managers and partners respectively. Despite that, fuzzy-Delphi and fuzzy-AHP are still considered as traditional fuzzy set methods, which cannot extract fuzzy rules from the history data. As a result, adaptive neuro-fuzzy inference system (ANFIS) is applied to increase the adaptive ability of a selection model (Shahhosseini & Sebt, 2011).

4.2. Cost/time/quality performance assessment (article number = 91)

4.2.1. Time, cost or quality performance assessment
Performance assessment is often described as a systematic way of measuring project performance by evaluating the inputs, activities and outputs regarding each project objective (e.g. cost, time and quality). A majority of researchers have tried to build frameworks that allow decision makers to better understand the situation of performance assessment without being overwhelmed by its complexity. Both quantitative and qualitative variables are involved when establishing frameworks to comprehensively reflect the assessment. Fuzzy logic (Gunduz et al., 2015) and its variants, such as fuzzy-ANP (Kabak et al., 2014) as well as fuzzy-AHP and fuzzy-TOPSIS (Li et al., 2017a), are widely used to deal with the uncertain and imprecise information during the assessment. Due to the complexity of performance assessment, it is difficult to define a specific functional equation. Without assuming a particular functional form, DEA (Tsolas, 2013) and its related hybrid methods, such as DEA-principal component analysis (PCA) (Iyer & Banerjee, 2016), and fuzzy-related hybrid methods, such as fuzzy-AHP and fuzzy-DEA (A. S. Loron & M. S. Loron, 2015), are also popularly used for identifying the benchmarks to compare the alternatives. To further imitate the decision making process in the human brain, evolutionary fuzzy neural inference model (EFNIM), which combines GA, fuzzy logic and neural network, exerts the advantages and avoids the drawbacks of each single method. Such a combined method can be used to solve the complex decision making problems, such as budget allocation performance (Cheng et al., 2008) and construction productivity forecast (Mirahadi & Zayed, 2016).

4.2.2. Trade-off
In construction projects, trade-off can be divided into time-cost-resource utilization optimization (TCRO) (Zahraie & Tavakolan, 2009), time-cost-quality trade-off (Diao et al., 2011), and time-cost-environment impact (TCEI) (Ozcan-Deniz et al., 2012). TCRO can be further divided into the resource-constrained project scheduling problem (RCPSP) that minimizes the time of project completion under resource restrictions and the resource leveling problem (RLP) that allocates resources under project completion time constraints (Li et al., 2018). The exact (i.e. enumerative, dynamic programming, linear programming, etc.), heuristics (i.e. inductive method, local search method, etc.), and metaheuristics methods (i.e. EMO, etc.) are often employed to solve the problems mentioned above (Eshtehardian et al., 2009). Compared to exact methods and heuristics, metaheuristics methods can more thoroughly explore the solution space and therefore are more flexible for the problems mentioned above. It is found in this research that two articles adopt heuristics methods while 13 articles utilize metaheuristics methods among a total of 15 articles on the trade-off problems. As the second generation of EMO algorithms, NSGA-II (Monghasemi et al., 2015) is the most popular metaheuristics method for the trade-off problems.

4.3. Design/system/method/project/portfolio selection (article number = 109)

4.3.1. Design selection
There is a growing body of literature that recognizes the importance of decision making during the design process (Tiwari et al., 2017). Since the design proposed by architects and designers is sometimes not conducive to construction contractors or not satisfied by customers and end-users, user-centered design has drawn an increasing attention recently. Compared to MADM methods, MODM methods provide more choices to customers for selection. For this reason, MODM methods, such as DEA (Cariaga et al., 2007) and case-based reasoning (CBR)-GA (Cebi et al., 2010), are mostly used to deal with user-centered design. Another important issue is the comparison of different design schemes according to predetermined criteria. Curiel-Esparza and Canto-Perello (2013) used AHP to select utility tunnels techniques. Reizgevicius et al. (2014) adopted hybrid TOPSIS multifunctional methods to evaluate 4D computer-aided design. In construction today, building information modeling (BIM) is widely recognized as a digital revolution. With the emergence of BIM, however, the number of possible design solutions increase markedly, which may cause impracticability for
determining the optimal solution (Inyim et al., 2015). In this case, stochastic optimization methods (e.g. NSGA-II) is often chosen to solve the complex design problem (Migilinskis et al., 2017), such as rock-fill dam design (Nikoo et al., 2015) and sewerage rehabilitation design (Lin et al., 2016).

4.3.2. Management system/construction method selection

Project management systems and construction methods play a vital role in project delivery and success. Instead of rigorous data, the selection of project management systems and construction methods is largely based on acquaintance and preference (Chen et al., 2010). MCDM and its integrated methods, which measure both tangible and intangible variables in intricate and varied circumstances, can handle the selection of project management systems and construction methods effectively and efficiently (Chen, 2018). Taking project delivery system (PDS) selection as an example, DEA and ANN (Chen et al., 2011), RST (Liu et al., 2015a, 2016a), fuzzy multi-criteria group decision making (FMCGDM) (Khanzadi et al., 2016), and interval-valued intuitionistic fuzzy set (IVIFS) (An et al., 2018) can be observed within the relevant literature. Although various studies have been conducted to explore the mechanism for the selection of appropriate tools, a common trend is the integration of MCDM methods and simulation technologies, which avoids the reliance on costly experimental tests or historical data. For instance, Khoramshokooh et al. (2018) explored cut-off wall selection with the combination of PROMETHEE and multi-layer perceptron (MLP) simulation model while Marzouk and Al Daour (2018) investigated labor evacuation of construction sites through the mass motion simulation platform based on TOPSIS.

4.3.3. Project/portfolio selection

Where the selection of a construction project is concerned, the client of the project should consider both financial and nonfinancial criteria when choosing the best project alternative (Dikmen et al., 2007). Establishing an objective evaluation model that can thoroughly evaluate the feasibility of each project alternative and determine its prioritization is paramount important. During the process of project selection, the traditional analysis fails to analyze qualitative attributes that cannot be easily expressed in monetary terms (Yan et al., 2011). To eliminate this limitation and meanwhile realistically and accurately measure the preference of decision makers, different intuitionistic fuzzy techniques are often used for project selection, such as intuitionistic fuzzy Einstein correlated averaging (IVIF-ECA), intuitionistic fuzzy TOPSIS (IFT) and dynamic intuitionistic fuzzy weighted averaging (DIFWA) (Gu et al., 2014; Ghoddousi et al., 2018). Since single project selection does not consider the interaction between projects (Ghapanchi et al., 2012), the selection of project portfolio has increasingly drawn research attention in recent years. For example, Abbasi-Jahromi and Rajaie (2012) selected a portfolio based on the risk endurable level while Ghapanchi et al. (2012) investigated the efficiency of project portfolio. The MCDM methods used for single project selection also apply to project portfolio selection.

4.4. Layout/location selection (article number = 56)

4.4.1. Network design/location selection

Network design refers to the decision making problem that determines the optimal planning, maintains the transport networks for different purposes, and reduces the negative impacts on environment (Zolfani et al., 2011; Miandoabchi et al., 2015). There are two types of relevant solutions for transport networks (i.e. alternatives). One is based on the use of MADM methods. For example, hybrid AHP (Zolfani et al., 2011) and fuzzy-TOPSIS (Liang et al., 2017b) are proposed to select from a limited number of predetermined alternatives. The other is based on the use of MODM methods. For example, GA and multi-objective B-cell algorithm (Miandoabchi et al., 2015) are adopted to obtain a set of Pareto-optimal solutions.

Project location is always restrained by a set of constraints and can be generally selected by three types of MCDM methods. The first is single or hybrid MADM methods, such as ELECTRE II (Dosal et al., 2012) and fuzzy-AHP (Ardeshiri et al., 2014a). The second is combined with spatial analysis techniques, such as geographic information systems (GIS) (Gumusay et al., 2016) and spatial database management system (SDBMS) (Diaz-Cuevas et al., 2018). The third is transforming the decision making problem, especially material source selection, into the classic transshipment problem, which can be solved by MODM methods, such as binary linear programming models (Jaskowski et al., 2014).

4.4.2. Site layout planning

Construction site layout planning and facility layout design are essential decision making processes during which available site facilities are allocated to free locations to deliver construction projects in a safer, more efficient and effective manner (Cheng & Lien, 2012; Ning et al., 2016). However, site layout planning and design represent a complicated task due to the conflicting objectives, diversity of decision criteria, and variety of possible solutions associated with construction projects (RazaviAlavi & AbouRizk, 2017). Compared to MADM methods, it is appropriate to utilize MODM methods to deal with site layout planning and design. The decision making framework can be generally divided into alternatives identification, layout optimization, evaluation and selection. During the process of alternatives identification, fuzzy logic is employed to address uncertain factors (Ning et al., 2011) or represent the closeness of facilities (Xu et al., 2016). The processes of optimization, evaluation and selection result in a set of elite site layout existed solutions that are both feasible (i.e., completely satisfy hard constraints) and qualified (i.e., sat-
isfy soft constraints to the highest levels). Since examining all possible solutions is almost impossible, metaheuristic optimization methods, such as PBA (Cheng & Lien, 2012), ACO (Adrian et al., 2015), multi-objective simulated annealing-based GA (MOGA) (Xu et al., 2016), and GA-based simulation optimization method (Lu et al., 2018) are taken to find the limited number of non-dominated solutions for further selection.

4.5. Material/equipment selection (article number = 35)

The appropriate use of construction material and equipment is a prerequisite to the quality and efficient execution of construction activities in a project (Cirovic & Plamenac, 2006; Rahman et al., 2012). Actually, the process of material and equipment selection is inherently a multifaceted cost and benefit trade-off, which is further compounded by the complexity and the unique context of the project (Shapira & Goldenberg, 2005; Goldenberg & Shapira, 2007). Some research attempts have been made for equipment selection, comparing equipment alternatives or estimating equipment parameters. The overwhelming majority is selecting the optimal equipment from a limited number of alternatives. For this reason, MADM methods are chosen predominantly for equipment selection. For example, fuzzy-TOPSIS method was adopted by Yazdani-Chamzini and Yakhchali (2012) for tunnel boring machine (TBM) selection while VIKOR, TOPSIS and PROMETHEE combined methods were employed by Masoumi et al. (2018) for monitoring instrument selection. Compared to MADM methods, article by Zhai et al. (2018) was the only within the reviewed publications using GA as a MODM method, which extracted load cycles of wheel loaders. Material selection is essentially the same as equipment selection, for which both MADM and MODM methods can be applied. Unlike equipment selection that mainly relies on MADM methods, MODM methods are more commonly adopted to determine the material ratio or combination for material selection. For example, AHP and multi-objective optimization models were recommended by Yepes et al. (2015) for the selection of reinforced concrete (RC) beams while AHP and fuzzy MOORA were introduced by Ilce and Ozkaya, (2018) for the selection of raised floor materials.

4.6. Risk/safety management (article number = 82)

The dynamic nature of construction projects results in circumstances of high uncertainty and risk (Taylan et al., 2014). Risk management is a pivotal component of the decision making process and plays a significant role in project success (KarimiAzari et al., 2011). It can be divided into three processes, namely risk identification, risk assessment and risk mitigation (Salah & Moselhi, 2016). During the three processes, MCDM methods are generally involved to achieve different purposes. As a particular area of risk management, safety management follows the general procedures of risk management and uses the MCDM methods for safety issues. Risk identification helps decision makers in a construction project to identify risk factors associated with the project. For example, Li et al. (2013) proposed an improved AHP method to identify risk factors during open-cut subway construction. Chien et al. (2014) applied DEMATEL to pinpoint risk factors when implementing new technologies in construction projects.

Based on risk identification, risk assessment evaluates the potential adverse effect. Risk assessment approaches range from classical methods to fuzzy set techniques (KarimiAzari et al., 2011). The classical ones refer to the quantitative methods using the loss expectancy theory, which describes a risk source as a function of possibility (likelihood) and consequence of its occurrence (Samantra et al., 2017). On the other hand, MCDM methods are adopted to calculate the weight of each risk factor, which may include fault tree analysis (Ardeshir et al., 2014b), probabilistic cost estimation process model (Cha & Lee, 2018), and Bayesian network model (Malekmohammadi & Moghadam, 2018). The information of risk is often uncertain and inaccurate in construction practice. For this reason, fuzzy set techniques are utilized to measure both quantitative and qualitative factors, taking the uncertainty and inaccuracy of factors into consideration during risk assessment. The basic idea is assessing both the significance of risk (SR) and the influence of risk (IR), and then ranking different risk factors based on SR and IR. Fuzzy set theory (Zhang & Zou, 2007), PFS (Wang et al., 2018), hesitant fuzzy sets (HFSs) (Zolfaghari & Mousavi, 2018) and 2-tuple linguistic neutrosophic EDAS (Wang et al., 2019) are proposed to carry out risk assessment under such circumstances.

In this research, there are only a few studies in which MCDM methods are adopted for risk mitigation, which tends to optimize risk response or risk allocation. For example, TOPSIS and K-nearest neighbor (KNN) techniques by Chen et al. (2012) and grey system theory by Chen et al. (2017) help construction material suppliers to handle the financial risk hedging with regard to the fluctuation in material prices and the variation in currency exchange rates or interest rates. It is worth mentioning that risk allocation can be considered as the nondeterministic polynomial (NP)-hardness problem. Therefore, GA (Fang et al., 2013; Alireza et al., 2014) and adaptive algorithm (Rahimi et al., 2018) are proposed to search the optimal solutions from a large number of candidates during a finite time.

4.7. Sustainability/environment assessment (article number = 71)

4.7.1. Sustainable performance assessment

Nowadays, the concept of sustainability is generally acknowledged to be crucial in the construction industry (Ghoddousi et al., 2018). Relevant research mainly focuses on the identification of sustainable performance index and the implementation of sustainability assessment. Sustainability in the construction industry can be treated as the
reconciliation of economic, environmental, and social dimensions (Torres-Machi et al., 2015). How to identify and balance the factors for each dimension becomes a major issue for decision makers (Cadena & Magro, 2015). MADM methods are dominant in relevant research to achieve this purpose. For example, interval-valued fuzzy set (Chen et al., 2015), weighted aggregated sum product assessment (WASPAS) (Gholipour et al., 2018), and fuzzy-DEMATEL–ANP approaches (Mavi & Standing, 2018) are employed to establish the sustainable performance index or sustainable assessment criteria. On the other hand, construction researchers apply MADM methods to assess the sustainable performance of construction projects or measure the improvement of construction sustainability, which can be seen from Antucheviciene et al. (2010) for revitalizing old buildings and Tan et al. (2014) for reducing construction wastes and saving natural resources. Besides the MADM methods mentioned above, integrated value model for sustainable assessment (Modelo Integrado de Valor para una Evaluación Sostenible – MIVES) (Pons et al., 2016) and MADM method based on value function (Pons & Aguado, 2012; Cuadrado et al., 2016) are also applied in the construction industry for sustainability assessment.

4.7.2. Environmental impact assessment

The construction industry accounts for a significant proportion of total resource and energy consumption. Therefore, it is necessary to access the environmental impact of construction projects and further achieve environmentally conscious construction by taking effective actions during construction projects (Liu et al., 2018). Based on generic frameworks for rating the environmental performance of buildings and projects, such as Building Research Establishment Environmental Assessment Method (BREEAM) in the UK, Leadership in Energy and Environmental Design (LEED) in the US and Green Star in Australia, localization and customization of assessment categories and criteria may be needed (Banani et al., 2016; Zarghami et al., 2018). MCDM methods, such as MAUT and TOPSIS (Seyis & Ergen, 2017), DEA (Vyas & Jha, 2017) and fuzzy-AHP (Zarghami et al., 2018) are often involved in the process of localization and customization. Since the measurement of life-cycle environmental impact focuses on the quantification of tangible and intangible factors, fuzzy logic, such as fuzzy-ANP (Ignatius et al., 2016), BIM-aided fuzzy-PROMETHEE (Chen & Pan, 2016), and vague set technique (Liu et al., 2018) are utilized in the construction industry.

4.8. Suitability of MCDM application in construction

A comprehensive analysis of the application of MCDM methods in construction shows that relevant research can be divided into decision making problems with a limited number of alternatives and those with a much larger number of alternatives. As for decision making problems with a limited number of alternatives, such as contractor (subcontractor)/supplier selection and material/equipment selection, MADM methods are more suitable under such a circumstance. Fuzzy logic is extensively used to accurately reflect uncertain information. Construction researchers tend to apply advanced fuzzy methods or fuzzy methods that are combined with other MCDM methods to solve decision making problems more effectively. On the other hand, many decision making problems in construction with a much larger number of alternatives, such as layout/selection, may be formulated as classical optimization problems that are purposed to obtain possible satisfactory solutions within practical time limits. MODM methods, especially single EMO methods and EMO methods that are combined with other MCDM techniques, gain growing popularity in this context.

5. Challenges and future research directions

5.1. Challenges and knowledge gaps in construction

According to the statistical analysis in Section 3 and the discussion in Section 4, this research finds some common challenges and knowledge gaps for the application of MCDM methods in construction. First of all, most of the reviewed studies have not taken the applicability of the model into account. This research reveals 29 single methods and 94 hybrid methods of MCDM. In fact, few reviewed studies have analyzed the potential requirements for using certain MCDM methods, such as the independence restriction of attributes, the amount and dimension of attributes, and the conversion of qualitative attributes. For example, VIKOR’s attributes should be independent of each other. However, none of the 17 studies on VIKOR reviewed in this research discusses the independence of attributes. The ignorance of the above requirements may lead to the inapplicability of the model or even wrong decision making.

Secondly, most of the reviewed works have ignored the robustness of the model. Few construction researchers have noted the following two concerns for applying MCDM methods in construction: (1) there is a potential risk of rank reversal error on adding or removing decision alternatives (Nazari et al., 2017); and (2) the use of different MCDM methods (especially MADM methods) may lead to different ranking orders (Zolfaghari & Mousavi, 2018). The two concerns reflect the rank reversal problem that is characterized by a change in the rank ordering of the preferability of alternatives when the chosen methods or the original alternatives change (Salabun et al., 2016; Ziomba & Wątróbski, 2016). The rank reversal problem is particularly true for AHP-related methods. Some other MCDM methods applied in construction (i.e. ANP, ELECTRE, TOPSIS, PROMETHEE, MAUT, etc.) also encounter the same obstacle. In reality, the overwhelming majority of construction studies have either neglected testing the problems and validating the results when decision alternatives change or avoided comparing the strengths and
performance of different MCDM methods in ranking alternatives.

Thirdly, the uptake of new MCDM methods in construction lags behind. An obvious lag between MCDM application in construction and that in general is identified when referring to the dendrogram of MADM (see Figure 1) and the dendrogram of MODM (see Figure 2). For example, the revised PROMETHEE-II methods based on Brans (1982) in general are still commonly utilized in construction in recent years, which can be seen from Cavalcante et al. (2017), Silva et al. (2017) and Wu et al. (2018a). On the other hand, NSGA-II proposed by Deb et al. (2002) in general is not widespread in construction until recently (Lin et al., 2016; Yang et al., 2017; Wu et al., 2018b). In other words, “postpone effect” exists in the application of MCDM methods in construction. It is found in this research that MCDM methods adopted in construction mostly combine antiquity and ease of application. AHP and fuzzy-AHP are still the most popular single method and hybrid method, respectively. By comparison, the newer and more advanced methods have not yet received enough attention and large-scale application in construction.

Fourthly, most reviewed publications have completed by the historical and static data. In reality, decision making environment and decision making data are not static. Instead, construction projects are managed under fast-changing conditions. However, working in a dynamic or predictable manner can be only seen from several publications in recent years, such as Zhang et al. (2019) that built a model based on interval-AHP and TOPSIS to identify the real-time safety risk of metro construction adjacent building, Latifi et al. (2019) that presented a framework according to the game theory and MODM to dynamically optimize low impact development practices for urban storm water management, and Chalekaee et al. (2019) that established a new hybrid model based on several MADM methods to address the future construction delay change response problem. Unfortunately, the vast majority of previous publications are purely structured on the historical and static basis. As a result, they lose the power in practice when making decisions.

Fifthly, little has been done for the scale problem in MCDM application in construction. The scale problem arises when adding criteria or alternatives cause a significant increase in both computational time and cost. It can be categorized into (1) a large number of criteria; (2) a large number of alternatives; and (3) a large number of both criteria and alternatives (Liu et al., 2015b). It is difficult for a single MCDM method to deal with the scale problem in large and complex situations. When the number of objectives is greater than 3, the consumption of computational resources, especially computational time, will increase exponentially following the increase in the number of objectives. Such situations will intensify in the context of big data. The construction industry is entering an era of big data. The rapid development of digital technologies in construction, such as BIM and GIS, makes the acquisition and processing of big data easier and more accessible. It can also be found in this research that many construction studies have integrated BIM and GIS into MCDM methods, such as AHP (Ristić et al., 2018), TOPSIS (Marzouk & Al Daour, 2018) and fuzzy DEMATEL (Gigović et al., 2017). However, the acquired data by BIM or GIS is not fully utilized due to the scale problem of these traditional MCDM methods. Therefore, the scale problem become one of the biggest challenges to the application of MCDM methods in construction.

5.2. Future studies on MCDM methods in general

MCDM in general has been developing with the emergence of different methods one after another. However, there are still some challenges that lie ahead (see Table 4). With regard to MADM methods, improving existing methods to make them more robust (see the conditions for robustness from Brauers and Zavadskas (2010)) demands future studies. New algorithms or frameworks should be proposed in the future for robustness improvement. In addition to robustness improvement, future research efforts should be made to address the impreciseness or uncertainty of information during decision making processes. Soft computing represented by fuzzy set, grey set and rough set has been increasingly adopted. Soft comput-

| Research challenges | Future studies |
|---------------------|----------------|
| MADM                |                |
| Less robustness     | New or advanced algorithm design |
| Impreciseness or uncertainty of information | Soft computing |
| Unstable situation  | DMADM          |
| Future aspects of issues | PMADM  |
| MODM                |                |
| Higher dimensionality | New or advanced algorithm design |
| Less robustness     | Hyper-heuristics and new algorithm design |
| Computationally expensive | Surrogate models |
| DSS for MCDM        |                |
| High volume, high velocity and high variety of the information | Interdisciplinary integration (MCDM methods and other techniques) |
|                     | Advanced DSS for MCDM |
gins, DSS could provide a useful platform or framework, handling big data and making existing MCDM methods well adapted to the complex situations of MCDM problems. In summary, interdisciplinary integration and advanced DSS (e.g., biometric and intelligent DSS) for MCDM problems indicate important research directions for the MCDM application in general (see Figures 1 and 2). More details can be found from Kaklauskas (2015) and Filip (2020).

5.3. Future research directions for MCDM in construction

Based on the identification of MCDM challenges in construction (see Section 5.1) and the analysis of future studies on MCDM methods in general (see Section 5.2), further research directions are discussed below for MCDM in construction. As mentioned above, little or no attention to the applicability of MCDM methods is the first and foremost challenge in construction. To address this challenge, construction researchers should take the requirements of the MCDM method itself into consideration. It is appropriate for them to make frameworks solid and complete. On the other hand, decision makers are encouraged to pay attention to the applicability of MCDM methods carefully so that they can have a good understanding of the preconditions for applying certain MCDM methods.

The robustness challenge can be addressed from both internal and external perspectives of MCDM methods. To solve the problems inherent within existing MCDM methods, such as the reversal problem that mainly stems from the difference between the scale used for pair-wise comparison of alternatives and the actual scale of measuring each criterion (Shapira & Goldenberg, 2005), future researches can be pursued in the following three ways: (1) adopting absolute measurement of alternatives instead of relative measurement; (2) ensuring decision makers’ understanding of pair-wise comparison; and (3) improving the aggregation procedure of existing preferences. It is also important for construction researchers to ensure that non-robust results are not caused by “garbage in, garbage out”.

"Postpone effect" is well known because construction lags behind in terms of MCDM research and application. Figures 1 and 2 show the evolutionary development of MADM and MODM, respectively. It is important for construction researchers and decision makers to embrace the cutting edge MCDM methods. Under the premise of equally applicable conditions, for example, BWM is superior to AHP and ANP (see Section 1.3.2) and NSGA III performs better than NSGA II (see Section 1.4.3). Another future effort lies in the application of soft computing techniques, especially the improved methods of fuzzy set, rough set and grey set and their combination with other advanced MCDM methods, to solve complicated problems of decision making in construction. When facing new certain MODM problems, it is also possible for construction researchers and decision makers to try hyper-heuristic and identify which heuristic method works more efficiently and effectively.
The lack of real-time and dynamic analysis challenges MCDM application in construction. Construction researchers and decision makers should focus on DMADM, PMADM relevant methods and MADM based scenarios, to overcome the reliance on the historical and static data as a common weakness in construction. The highlight of real-time and dynamic analysis not only addresses the challenge of the historical and static data but also provides a solution to the challenge of the “postpone effect” because new and advanced techniques are introduced into decision making.

In order to deal with the scale problem, it is possible to pursue research on decomposition based EMO methods that transform original problems into several single-objective optimization problems and indicator-based EMO that does not have scalability limitations compared to conventional Pareto based EMO. For the high dimensional search space and expensive objective functions for real-world complicated construction problems, research attention can be paid to surrogate models for evaluating the fitness functions to save calculation costs. Other possible solutions are external, that is, making use of interdiscipli- nary integration and advanced DSS. For the former solution, the integration of MCDM methods and emerging techniques (e.g. AI) can process the large volume data in construction to a certain extent. For the latter solution, advanced DSS can assist MCDM methods to collect and handle the big data of construction projects more sufficiently, comprehensively and agilely. With regard to interdisciplinary integration and advanced DSS as new and promising areas, Pan and Zhang (2021) and Marcher et al. (2020) summarized the frontier and exploratory research in construction recently. In the future, more and closer attention should be given in construction to relevant research on interdisciplinary integration and advanced DSS for MCDM.

Conclusions

Decision making is a critical process to achieve success in any sectors, especially in a sector like construction that requires handling numerous information and knowledge. MCDM methods contribute to appropriate decision making in general as well as in construction. They can be divided into MADM and MODM methods. This research first analyzes the evolutionary development of MADM and MODM in the general sense. A total of 530 construction articles published between 2000 and 2019 are then reviewed using the proposed methodology of SLR. Based on the SLR, this research offers a systematic and thorough understanding of MCDM application in seven construction areas. It is found from the analysis of relevant literature that various MCDM methods have developed in recent years at a faster rate and meanwhile there is a tendency toward cross-integration, which allow construction to adapt itself to increasingly complex environments.

In this research, the results of the literature review show the ever-growing popularity of MADM methods since 2005. This is because, compared to MODM methods, MADM methods generally require a smaller amount of data to deal with decision making problems. As a result, it is more practicable and possible. According to existing studies, AHP and fuzzy logic are more commonly used for construction decision making problems than other single methods. On the other hand, fuzzy-AHP and fuzzy-TOPSIS are two dominant hybrid methods. Compared to single methods, hybrid methods become more promising. It is found in this research that MCDM methods can be mainly applied in seven construction areas (namely seven major themes) for decision making problems, ranging from contractor (subcontractor) / staff / supplier selection to sustainability/environment assessment. The finding of this research implies the penetrating involvement of MCDM in almost every aspect of construction decision making.

The development of MCDM research in construction is never stopped. This study identifies the potential challenges of the current MCDM research in construction, including the applicability concern, robustness problem, postpone effect, dynamic and prospective challenge, and scale problem. Subsequently, it presents the future directions for MCDM research in a new era. The new MCDM methods, such as soft computing, AI and other modern techniques, are expected to play important roles in addressing the above challenges for decision making in construction. The ultimate reason is not only the advancement of MCDM methods but also the complexity of construction problems.

Overall, this research adds value to the body of MCDM knowledge in three ways:

- It reveals the evolutionary development of MADM and MODM methods by retroactively classifying and deeply investigating the mainstream methods. Compared to previous studies, it updates the body of MCDM knowledge and adds the latest and most significant methods to the dendrograms (see Figures 1 and 2).
- It proposes a novel methodology of SLR to objectively explore the progression of MCDM in construction. The bibliometric analysis and discussion further provide researchers and practitioners with an intuitive understanding of the MCDM application status in different key areas.
- For the application of MCDM methods in construction, this research identifies the challenges and knowledge gaps. It also highlights the future research directions accordingly. These can provide insights and inspirations to construction research and practice in the MCDM context.

The SLR methodology proposed in this research has some strengths: (1) it can provide an evidence-based review, which seeks to comprehensively cover the subject to explore the body of literature; (2) the exclusion procedure depending on statistical non-parametric test can produce unbiased results to the greatest extent; and (3) the theme identification based on content co-occurrence analysis can
objectively permit the accurate assessment and identify the application status. However, this research has certain limitations. Firstly, the scope of MCDM methods included in this research is limited to the mainstream methods. Although a large number of MCDM methods have emerged in recent years, it is impossible for this research to cover every method. Noteworthily, it does not mean that the methods excluded in this research have no importance. Secondly, the articles are collected from the journals in the Web of Science during the period from 2000 to 2019. The articles published in non-SCIE and non-SSCI journals are excluded. Meanwhile, conference articles, books and dissertations are not considered in the literature sample. Finally, the majority of existing studies on DSS for MCDM in construction mainly focus on system frameworks rather than MCDM methods and therefore they are not reviewed in this research. Due to all these reasons, future research is recommended through the collection and review of relevant literature from a wider range.

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