Decision Support in Building Construction: A Systematic Review of Methods and Application Areas

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Abstract: Decision making is a relevant task in the building construction sector, and various systems and methods for decision support are emerging. By means of a systematic literature review, this article identifies the methods for decision making in building construction and the lifecycle phases for which decision support systems are proposed. The selected articles are analyzed and grouped according to the adopted decision-making methods and the defined lifecycle phases. The findings show that multiple criteria decision analysis is the most used method for decision support in building construction and that the construction phase is the most addressed phase within the relevant existing works. The findings related to the construction phase are further refined by grouping the articles into application areas and by reviewing in detail the proposed methods therein. The scarce availability of data and project cases is identified as the most common barrier for the successful development and implementation of decision support systems in the building construction sector. This work provides a basis for scientists and practitioners for identifying suitable methods for decision-making support in a specific lifecycle phase of a building.

Keywords: decision support systems; decision making; building lifecycle; construction phase; methods; applications

1. Introduction

The adoption and development of computer and information technology for supporting decision-making activities is gaining importance in many business sectors. In particular, the increasing availability of digital data leads to an increased demand for computer technologies that can support decision making [1]. Construction is a business sector where adequate decision making is one of the key factors to achieve success [2]. Here, decision making is characterized by a high complexity [3], and there is an increasing need for adopting systems that can support these operations [2]. The use of computer technology for decision support is thus promising to improve the quality and efficiency of building construction processes.

Decision making is based on available knowledge and information and can be considered as an evaluation of the potential effects of alternatives [3]. As construction projects are usually one of a kind, the available alternatives are evaluated on a project basis. The evaluation of alternatives should consider not only available information, but also the preferences and the knowledge of experts [4]. Decision making in such an environment is a challenging task and computerized systems for decision making can support decision makers in the evaluation and the assessment of the available alternatives. Computer technologies that support decision-making activities are called information systems for decision support or decision support systems. The term information systems for decision support was first introduced by Gorry and Scott Morton in 1971 [5]. Nowadays, decision support systems can be

defined as 'interactive computer-based systems that help people use computer communications, data, documents, knowledge, and models to solve problems and make decisions' [6] (p. 1). Traditionally, decision support systems consist of the following four fundamental components: (i) the user interface component, that contains the necessary information for the interaction with the user; (ii) the database component, that stores data and knowledge; (iii) the model component, that contains the models and the inference engine; and (iv) the communications component, that contains the architecture and the network of the decision support system [6]. These interactive computer-based systems evaluate available alternatives by employing formal and non-formal methods for decision making. These methods of decision making can facilitate decision making in every lifecycle phase, from the development of the first concept to deconstruction [7]. Multiple criteria decision analysis (MCDA) is a formal method for decision making that finds many applications in the construction sector [2,7,8]. This method supports decision making in situations with multiple and often conflicting objectives [2] with the aim of identifying the best compromise. These formal methods have already been widely implemented in engineering systems and are broadly applied in decision-making problems of the construction sector [7]. Additionally, many non-fully formal methods for decision making are employed in building construction. Within this review, we consider the following non-fully formal methods: fuzzy methods, that handle uncertain information by measuring degrees of truth of propositions [9]; machine learning techniques, that can be used for learning [10], extraction of information and making predictions [11]; genetic algorithms, that emulate processes of natural selection [12] for engineering optimization problems [13]; Bayesian methods that solve problems under uncertainty and form the basis for probabilistic reasoning approaches in the field of artificial intelligence [14]; mixed methods, where two or more methods are combined; and several other methods that found only a few or individual known applications.

As the number of publications in the field of decision support systems in the construction sector is growing, it is advantageous to exploit this existing knowledge for the conception and the development of new systems for decision support. Existing decision support systems employ different methods for decision making to address specific problems in the construction lifecycle. To make this information on existing decision support systems available, we provide a comprehensive review of the application areas of decision support systems and the most used methods for decision making in the building construction sector. To achieve this objective, we systematically analyze the literature in this field by addressing the following main research questions:

RQ1: Which methods for decision making are employed within decision support systems in the building construction sector? Rationale: Decision support systems employ different methods for decision making. The objective is to identify which methods for decision making are used, to categorize them and to show which are the most prevalent.

RQ2: In which phase of the building lifecycle phases are existing decision support systems applied? Rationale: Decision support systems can be applied throughout the whole lifecycle of a building. The objective is to identify which is the most suitable building lifecycle phase for decision support.

The results of this first part of the review are presented by organizing the relevant literature according to decision-making methods and building lifecycle phases. This categorization and a compact representation of the results provides immediate information on the type of methods for decision support adopted (RQ1) and of the phases (RQ2) in which these are applied. Preliminary results of the review showed that most of the decision support systems are dedicated to the construction phase. For this reason, this phase is further analyzed, and the following additional research questions are formulated:

RQ3: Which are the proposed applications of decision support systems in the construction phase? Rationale: Most of the existing decision support systems are proposed for the construction phase. The objective is to identify the most suitable applications for decision support in the construction phase and to highlight the gap for future applications.

RQ4: Which are the strengths and limitations of the methods proposed for the construction phase? Rationale: Additionally, in the construction phase, different methods are proposed for decision support. The objective is to highlight potential benefits of the specific methods applied in the construction phase.

The results of this detailed analysis of the construction phase are presented by means of a matrix that represents the selected literature according to methods and application areas. This representation enables us to detect which are the most suitable application areas (RQ3) of decision support systems in the construction phase. The strengths and limitations of the employed methods (RQ4) are highlighted to offer support in the selection of suitable decision-making methods for the construction phase. The remainder of this article is structured as follows: Section 2 depicts the research strategy and describes the adopted steps. Section 3 describes the results of the analysis and provides the answers to the research questions. Section 4 discusses the results, and Section 5 draws the conclusions.

2. Research Strategy

A systematic literature review is chosen as a research method. This research method requires the formulation of research questions and an exhaustive explanation of the performed steps that provide the answer to such questions [15]. The research strategy is described within a review protocol that is defined before performing the research and the review [16,17]. Our adopted review protocol is shown in Figure 1 and consists of three main phases: (i) data collection, where we collect the available literature in our field of study; (ii) screening, where we select the relevant literature by applying inclusion criteria; and (iii) analysis, where we refine our selection by applying additional inclusion criteria, define the data that need to be extracted to allow the classification of the selected literature, and create the basis for providing the answers to the research questions. The steps performed within the review are described in detail in the following subsections.
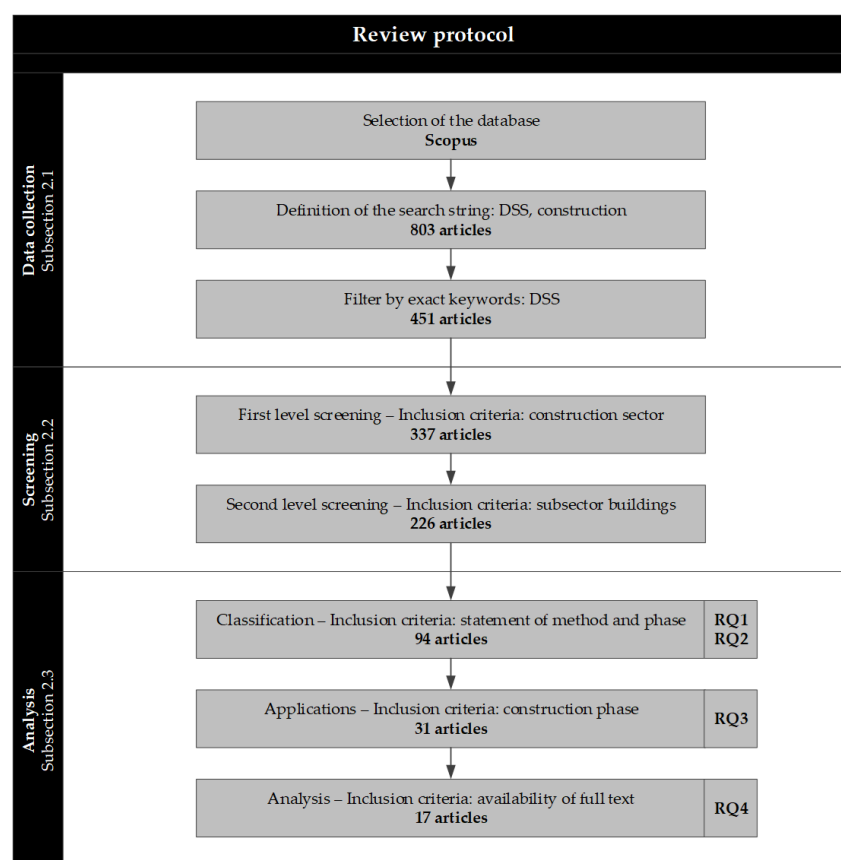

Figure 1. Our adopted review protocol.

2.1. Data Collection

This phase of the review aims at collecting the relevant literature in our field of study. To ensure the quality of the selected data, we considered the Scopus database for the collection of the relevant literature. According to the subject of study and the defined research questions, the main keywords are "Decision Support System" and "Construction". The literature is collected by searching the fields article title, abstract and keywords from January 2010 until March 2020. The research is limited to English articles within the subject area engineering. The resulting search string contains the Boolean operators "AND" and "OR" for searching the main keywords. The search items and the resulting search string are represented in Table 1. After inserting and applying the search string in the selected database, we find a total of 803 articles. Next, the collected data are limited to documents that contain the exact keyword "Decision Support System" or a corresponding synonym. The following synonyms were accepted: "Decision Support Systems", "Decision Support Tools" and "Decision Support System (dss)". This reduces the number of articles to 451. These articles are admitted to the screening phase.

Table 1. Search items and search string.

Item	Content
Keywords	Decision Support System, Construction
Database	Scopus
Search fields	Article title, abstract, keywords
Years	January 2010 to March 2020
Subject area	Engineering
Language	English
Document type	Article
Search string	(TITLE-ABS-KEY (decision AND support AND system AND construction) AND LANGUAGE (english)) AND (LIMIT-TO (SUBJAREA, "ENGI")) AND (LIMIT-TO (DOCTYPE, "ar"))

2.2. Screening

We consider two levels of screening. The first level of screening has the objective to select the articles that are dedicated to the construction sector. Title and keywords are screened and articles that are not related to the construction sector are disposed. This reduces the number of articles to 337. The second level screening has the objective to select the articles that are related to the building's subsector. The screening of title, abstract and keywords allows us to identify and dispose articles that are dedicated to the subsectors of infrastructure construction and industrial construction. This leaves us with a selection of 225 articles that are related to the subsector of building construction. These articles are admitted to the analysis phase.

2.3. Analysis

This phase of the review concerns the analysis of the selected articles and forms the basis for the formulation of the answers to the research questions. First, the criterion for inclusion in the analysis is applied. The criterion for inclusion to the analysis is that title, abstract or keywords contain a clear statement of the method applied within the decision support system. The analysis of title, abstract and keywords allows us to select 94 articles that respect the previously defined criterion. These articles are analyzed and categorized to provide the answers to RQ1,2. Next, the 31 articles related to the construction phase are selected. An in-depth analysis of title, abstract and keywords allows to provide the answer to RQ3. Finally, full papers are collected, and the available 17 full texts are analyzed to formulate the answer to RQ4. The results of the analysis phase are presented in Section 3.

3. Results

In this section, the selected literature is described and categorized, and the answers to the research questions RQ1–4 are provided. The results section is divided into the following subsections: (i) data description; (ii) decision support in building construction (RQ1–2); and (iii) decision support in the construction phase (RQ3–4).

3.1. Data Description

The bibliometric analysis of the selected 94 articles provides information about the trends in this research topic. Figure 2 shows the number of articles from 2010 to 2019. The selected data also contain 10 articles from January to March 2020 that are not included in Figure 2.
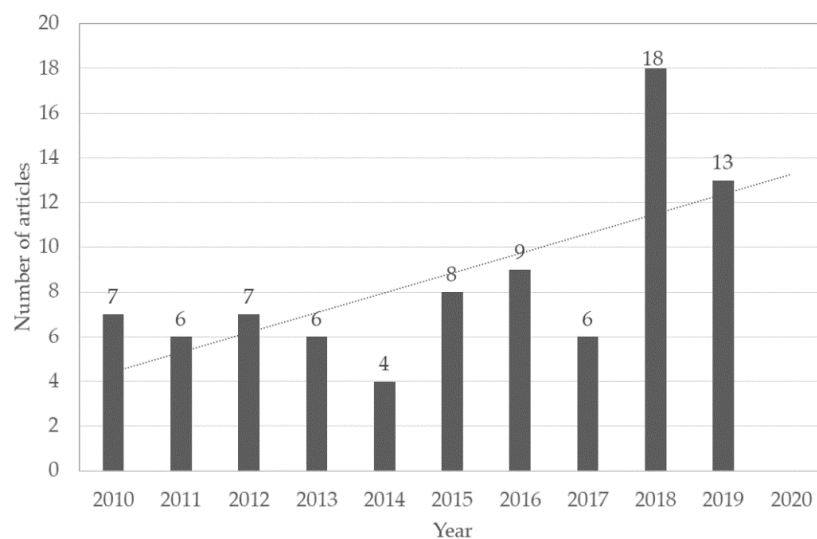

Figure 2. Selected articles organized by year of publication.

All the selected articles belong to the subject area engineering and to additional subject areas such as business, management, and accounting, followed by the areas of computer science and environmental science. Figure 3 shows how the articles are distributed by subject areas that differ from engineering. The bibliometric analysis of the literature shows an increasing interest towards the adoption of decision support systems for decision problems in the field of management and automation in construction.
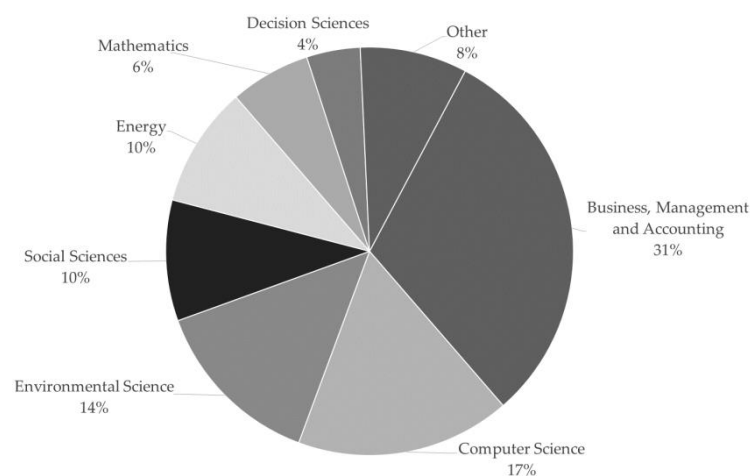

Figure 3. Articles per additional subject area.

3.2. Decision Support in Building Construction

This subsection provides the answers to the research questions RQ1 and RQ2. First, we introduce the categories of methods for decision support and the lifecycle phases that we identified within the review. These categories are considered for the organization of the articles according to the method and the lifecycle phase for which the decision support systems are proposed. The categorization forms the basis for the formulation of the answers to the research questions.

3.2.1. Existing Methods for Decision Support

The analysis of the selected articles allows us to define seven categories of methods. In the following subsection, the identified categories are introduced.

MCDA is a discipline of operations research and supports decision making in complex situations when multiple and conflicting objectives are present [2]. Many different approaches and techniques are proposed in literature, often also in combination one another. Within this group of methods, the decision maker plays an important role, as they aid the identification of the best compromise by incorporating subjective information, leading to different outcomes for every decision maker [18]. MCDA methods can be classified by linking them to the decision problems that they solve. Ishizaka and Nemerey group the most popular methods into methods that aid choice, ranking, sorting and description problems, and introduce already available software packages [18]. Other authors group MCDA into two main categories of methods: (i) multi attribute methods, in which a utility function is maximized, and (ii) outranking methods that consider pairwise comparisons of actions [19,20]. The analytical hierarchy process (AHP) belongs to the multi-attribute category and has received much scientific interest. This method found large applications in construction using both single and hybrid application approaches [2]. Within the category of outranking approaches, we find PROMETHEE, that provides rankings of the available actions based on preferences, and the group of ELECTRE methods, that can be applied to a wide range of decision problems [18]. A comprehensive overview of MCDA methods can be found, e.g., in [18,19].

Fuzzy methods include fuzzy logic and fuzzy set theory. Fuzzy logic has its origins in fuzzy set theory proposed by Lotfi Zadeh in 1965 [21]. The aim of this technique is to emulate imprecise or approximate human reasoning under uncertainty by enclosing partial truths [9]: traditionally, a proposition can be either true or false, and in fuzzy logic the uncertainty is represented by attaching numerical values that allow us to measure the degree of correctness of a proposition. Machine learning techniques are used for filtering, searching, detecting and predicting data in many different application areas [11]. Machine learning comprises not only the extraction of information but also learning from data with the aim to develop a program that is able to represent the data [10]. These techniques use also concepts from probability theory to model uncertainty in engineering problems [10,11]. Genetic algorithms are a subset of evolutionary algorithms that are inspired by the evolution of living organisms [13]. John Holland introduced this programming technique in the 1960s and further developed it to define a classifying system that reacts when specific conditions are satisfied by data [12]. Genetic algorithms were developed for optimization problems in engineering and rely on biologically inspired operators that are called crossover, mutation and inversion [13] and aim at emulating the processes of natural selection [12]. Bayesian methods are statistical techniques for solving problems under uncertainty. Bayesian statistics is a field of statistics that is based on Bayes interpretation of probability. Reverend Thomas Bayes (1702–1761) proposed a new rule that allows one to calculate posterior probabilities given evidence [22]. This rule is called Bayes' rule and is the basis for many probabilistic reasoning approaches in the field of artificial intelligence [14]. The category of mixed methods comprises methods that use two or more techniques in combination. Within this category, the most used group of methods are fuzzy MCDA and fuzzy methods in combination with other techniques. Furthermore, other main methods are combinations of these methods. The category of other methods encloses all the techniques that are proposed less than three times and according to the first screening do not fit within the other categories. In this category fall, for instance, case-based

and rule-based reasoning, programming techniques, critical path methods, analytical algorithms, multiagent systems and building information modelling (BIM)-based decision support.

3.2.2. Lifecycle Phases

For the categorization of the selected articles, we consider a division of the building lifecycle in phases. The building lifecycle consists of closely connected stages and there exist many different processes or plans that divide the lifecycle in phases. Variations of the building lifecycle depend on the type of project, the type of client, and on the delivery system. Often, the building lifecycle is simply broken down into the following main phases: project inception or brief, design, construction, and operation and maintenance [23–27]. Even if there exist several differences between process maps or plans of work, the core phases are the same [27]. According to the proposed divisions of the lifecycle in the literature, we consider the following phases:

- Development: This phase concerns the definition of the strategy to meet the client requirements and the initiation of the project. We consider applications that are relevant for the project development and for the client team.
- Design: Within this phase, the architectural concept, the spatially coordinated design, and the technical design with all the information that is necessary to construct the building are defined, regardless of the procurement strategy. Within this phase, we consider the applications that are relevant for the building design and for the design team.
- Construction: Within this phase, the building system is manufactured, constructed, and commissioned. We consider the applications that are relevant for the construction of the building and for the construction team.
- Operation and maintenance: Within this phase, the activities related to handover, and the use, operation and maintenance of the building are considered. Within this phase, applications are relevant for different actors in the building lifecycle.
- Cross-phase: It is likely that there will be an overlapping between different phases. For this reason, we use this category for collecting all the applications that cannot be associated to one phase.

3.2.3. Categorization of Articles

The selected 94 articles that passed the inclusion criteria are used for the categorization of methods and building lifecycle phases. The in-depth analysis of titles, abstracts and keywords allows us (i) to identify the techniques used within decision support systems and to group them into methods for decision making (RQ1) and (ii) to identify the main building lifecycle phases in which the decision support systems are applied (RQ2). The matrix in Table 2 represents our proposed categorization of the 94 articles according to method and lifecycle phase. For the categorization of the articles, we consider the following main methods: MCDA, fuzzy methods, Bayesian methods, machine learning, genetic algorithms, mixed methods, and other methods. We consider the simplified division of the building lifecycle into the following main phases: development, design, construction, operation and maintenance, and the category cross-phase. In Figure 4, we show the number of articles per lifecycle phase and method.

Table 2. Categorization of articles with methods and phases.

	MCDA	Machine Learning	Fuzzy Methods	Genetic Algorithms	Bayesian Methods	Mixed Methods	Other Methods
Development	[28–33]	[34,35]		[36]		[37–40]	[41–43]
Design	[44–51]	[52]		[53–55]		[56–64]	[65–68]
Construction	[69–75]	[76]	[77–79]		[80–82]	[83–93]	[94–99]
Operation and Maintenance	[100–104]	[105]				[106,107]	[108,109]
Cross-Phase	[110,111]	[112]	[113,114]	[115]		[116,117]	[118–121]

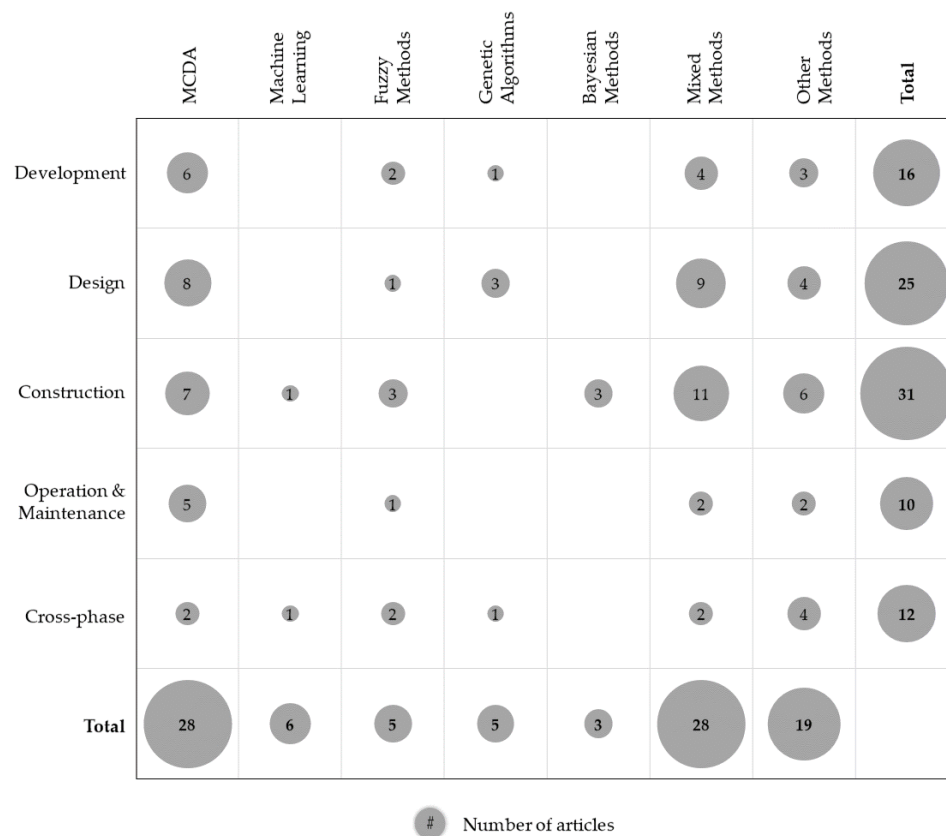|	MCDA	Machine Learning	Fuzzy Methods	Genetic Algorithms	Bayesian Methods	Mixed Methods	Other Methods	Total
Development	6		2	1		4	3	16
Design	8		1	3		9	4	25
Construction	7	1	3		3	11	6	31
Operation & Maintenance	5		1			2	2	10
Cross-phase	2	1	2	1		2	4	12
Total	28	6	5	5	3	28	19	

\# Number of articles

Figure 4. Number of articles per lifecycle phase and method.

3.2.4. Methods for Decision Support Employed within Decision Support Systems (RQ1)

The proposed categorization and the analysis of the articles identifies the most common methods for decision support and shows how frequently they are proposed within decision support systems. The results show that formal MCDA methods are predominant in building construction. The second most used category in terms of frequency of application are mixed methods. With respect to the proposed categorization, we see that we have a homogeneous distribution of the applications of the remaining methods for decision making. Fuzzy methods, machine learning, genetic algorithms and Bayesian methods are rarely employed within decision support systems compared to the application of formal methods. Within the category other methods, we find several individual or limited applications of decision-making methods.

3.2.5. Applications of Decision Support Systems in the Building Lifecycle Phases (RQ2)

The results of the analysis show how frequently decision support systems are proposed in a specific building lifecycle phase according to our proposed categorization. Most of the applications of decision support systems are proposed for the construction phase and the design phase. Less applications are proposed for the development phase and for the operation and maintenance phase. In the following, we list the applications that are proposed for the different lifecycle phases.

Development phase:

- Cost estimation, budgeting, and profitability assessment [31,34,38,39,43];
- Urban planning [29,35,36,42];
- Early evaluation of modularization and industrialization strategies [28,30,33];
- Sustainable project selection and classification [37,41];
- Determination of the appropriate procurement method [32];
- Dispute classification in the initial phase of private public partnerships [40].

Design phase:

- Sustainable planning and design [52,56,57,59,60,62,63];
- Building envelope design, optimization, and selection [45,49,54,66–68];
- Material selection [48,50,51];
- Evaluation of design alternatives [47,55];
- Installation of solar thermal power [44];
- Policy selection for the planning phase [46];
- Automated design and modelling [53];
- Mitigation of decision-making problems faced by a design team [58];
- Design optimization [61];
- Design team selection for design firms [64];
- Management of design changes [65].

Construction phase:

- Supply chain management and material procurement [71,75,86,90,91,94];
- Construction contracts and bidding [73,74,76,81,97];
- Equipment and logistics [72,83,89,99];
- Hazard analysis and safety planning [78,92,95,98];
- Project duration and scheduling [70,79,82,85];
- Optimization, performance and management of modular construction projects [69,80,84,96];
- Making decisions regarding overseas construction projects for companies [77];
- Environmental assessment and optimization [87];
- Software selection for the execution phase [88];
- Entropic risk analysis [93].

Operation and Management:

- Renovation [102,107,108];
- Retrofit and modernization strategies [100,103,104];
- Refurbishment [101];
- Predicting the remaining compressive strength [105];
- Assessment of building energy performance [106];
- Sustainable renewal of the building stock [109].

Cross-phase:

- Time and cost optimization [115,118–121];
- Contractor prequalification and selection [113,116];
- BIM software selection [110];
- Knowledge management [111];
- Evaluation of alternatives [114];
- Differing site condition litigations [112];
- Conflict resolution [117].

3.3. Decision Support in the Construction Phase

This subsection provides the answers to the research questions RQ3 and RQ4. The articles dedicated to the construction phase are selected from Table 2, and the results are further detailed. First, introduce the application areas for decision support in the construction phase that we identified within the review. These categories are considered for the organization of the articles according to method

and the application area for which the decision support systems are proposed. This categorization allows us to show the most common application areas in the construction phase (RQ3) and forms the basis for the analysis of the most common and effective methods for decision support (RQ4).

3.3.1. Application Areas and Categorization (RQ3)

The analysis of the remaining 31 articles allows us to identify the proposed application areas in the construction phase. According to the application list identified in Section 3.2.5, we use the following main application areas for further categorization and analysis of the construction phase: supply chain and materials, contracts and bidding, equipment and logistics, hazards and safety, scheduling and duration, modular construction, and other applications. The categorization of the articles according to application areas and methods is represented in Table 3. Furthermore, we show the number of articles per application areas and method in Figure 5. We find an equal distribution of the applications in the different phases.

Table 3. Construction phase. Categorization of articles with application areas and methods.

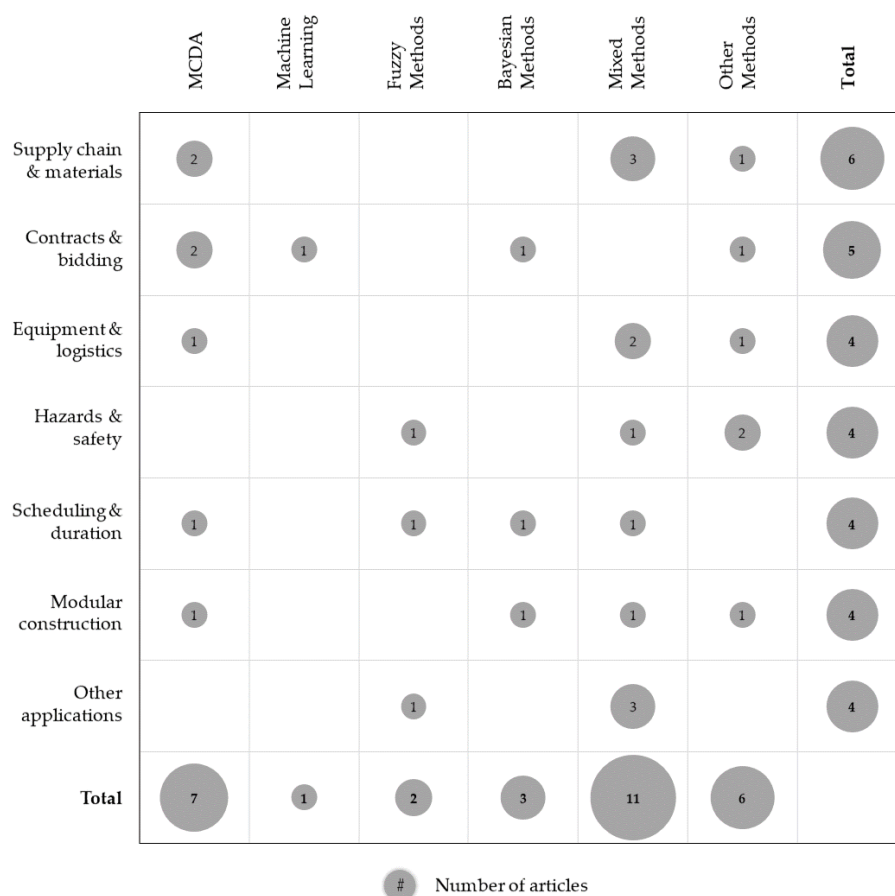|	MCDA	Machine Learning	Fuzzy Methods	Bayesian Methods	Mixed Methods	Other Methods
Supply chain and materials	[71,75]				[86,90,91]	[94]
Contracts and bidding	[73,74]	[76]		[81]		[97]
Equipment and logistics	[72]				[83,89]	[99]
Hazards and safety			[78]		[92]	[95,98]
Scheduling and duration	[70]		[79]	[82]	[85]	
Modular construction	[69]			[80]	[84]	[96]
Other applications			[77]		[87,88,93]	

Figure 5. Construction phase. Number of articles per application area and method.

3.3.2. Strengths and Limitations of Decision Support Methods for the Construction Phase (RQ4)

Seventeen full articles are available for the analysis of strengths and limitations of the proposed methods for decision making in the construction phase. Genetic algorithms do not longer appear among the methods. The following paragraphs present the results of this analysis for each of the proposed methods.

MCDA is the most used method for decision support in the construction phase. Two full papers are available for the analysis. Both are dedicated to the application area supply chain and materials. Here, this method finds application in the sustainable selection of concrete supplementary materials [71] and in the selection of appropriate suppliers [75]. It is shown that AHP can represent dependencies appropriately and that the analytical hierarchy process is efficient in comparing alternatives when the requested accuracy is low [75].

Machine learning is proposed within one paper dedicated to the area of contracts and bidding. Here, a neural network model is used for estimating project overheads based on past project cases [76]. When past project cases are available, the proposed decision support system can provide quick estimates also when data are imperfect [76].

Three applications of fuzzy methods are proposed, and one full paper is available for the analysis. The paper proposes an application for quantifying the probability of delay for contractors [79]. The main strength of the method is the ability to deal with incomplete and uncertain data and the consideration of expert knowledge [79].

Bayesian methods are proposed within three papers, and one full paper is available for the analysis. Bayesian inference with the Markov chain Monte Carlo-based numerical approach is used for updating input models in the construction phase [82]. This approach allows to deal with uncertainties, to integrate expert knowledge, and to use past data in combination with new observations [82]. The practical application is challenging because of the large amount of data and information that must be considered within this approach [82].

Mixed methods are the second category in terms of frequency of applications in this phase, and seven full articles are available for the analysis. Here, techniques are combined or applied in different modules of a decision support system to optimize results. Within the area materials procurement and supply chain management, a hybrid Bayesian fuzzy game is proposed to support price negotiation between contractor and supplier [91]. This combination allows one to use incomplete past data for making prediction on preferences [91]. Within the area of equipment and logistics, mixed methods are used for the selection [89] and the re-planning of lifting paths [83] of tower cranes. The combination of genetic algorithms, oriented bounding boxes and BIM models allows one to develop a decision support system that can operate with dynamic environments [83]. Within the selection problem of tower cranes, the results can benefit from the combination of BIM, genetic algorithms and AHP [89]. The combination of machine learning methods with MCDA is used for making predictions based on experience in the field of occupational accidents [92]. The combination of the analytical network process with different mathematical models allows one to integrate expert knowledge and rank variables for making predictions on the project duration considering the impact of weather [85]. The combination of fuzzy methods with equivalent noise summation and algorithmic mapping is used to develop a BIM-based framework for comparing the performance of modular and conventional construction methods [84]. Within the area other applications, lifecycle assessment and particle swarm optimization are combined to select construction schemes based on environmental metrics [87]. Here, the integration of additional methods in traditional lifecycle evaluations allows one to enhance and support computation and assessment of many alternatives [87].

Other methods are proposed within five full articles. Many individual applications of methods are proposed. Within the area of material procurement and supply chain, BIM is proposed for the selection of sustainable construction material sources [94]. Within the area of equipment and logistics, the traveling salesman problem is used for optimizing crane operations [99]. Within the field of modular construction, programming models can be applied for optimization problems as they can

account for uncertainties and determine the optimal supply chain configuration [96]. Within the field of hazards and safety, the application of reasoning systems supports in the design of fall protection systems [98], and BIM supports the automation in safety planning [95].

The limitations of the methods, when discussed, are consistent between the different methods. One common limitation is the availability and the processing of data and project cases [76,82,87,98]. The ability of processing and considering expert knowledge and preferences is considered as a strength [79,82,85,91] but in some cases also a challenging task [82].

4. Discussion

The review confirms an increasing interest towards development and application of decision support systems in the field of management and automation in construction. The complexity and the relevance of decision support systems for this sector is reflected by the wide range of applications that are proposed for every lifecycle phase. Several methods and approaches are already successfully employed within decision support systems. For the development of decision support systems, it is crucial to select the appropriate method given the problem at hand, because every method has different abilities and limitations.

The results show that formal MCDA approaches are the preferred methods for building decision support systems in every lifecycle phase. This result is confirmed also by other studies in this field [2,7,8]. The findings of this review show that these methods are used for the identification of the best compromise when multiple conflicting objectives are present [33,50], and they are used to order, rank, and prioritize the available alternatives [33,51,71]. The results also show extensive use of mixed methods for addressing decision problems in the building lifecycle. The combination of two or more methods allows us to optimize results or to apply different techniques in different modules of a decision support system. Moreover, within in this category, MCDA is frequently adopted in combination with other methods [48,71,75,85,89,92]. This extensive use of hybrid MCDA approaches in construction is also confirmed by previous studies [2,7,8]. The large popularity of MCDA can be exemplarily described by highlighting the key features of AHP. AHP has been identified as the most popular MCDA method in the construction sector. AHP convinces through its ease of use and its flexibility that allows the application to a wide range of problems without the need for great expertise [2]. AHP can be easily combined with other methods and is frequently used for defining the importance of the decision criteria [2,8]. MCDA methods are more successful when they are easy to use and when they have already had large applications, because this generally leads to time savings, but the increasing use of mixed methods also shows that they are often insufficiently equipped to address decision problems as a single approach [2].

Less applications are found for all the other methods. Machine learning techniques are useful for making estimations and predictions based on past data and project cases [76,105,112]. These techniques have the ability the ability to handle large amounts of datasets [34]. Fuzzy methods and Bayesian methods are used when uncertainties are considered. The main strength of these methods is their ability to deal with incomplete and uncertain data [79,82,113] and to integrate expert knowledge [79,82]. The combination of both methods allows one to consider past data for making predictions on preferences [91]. The limitations of the used methods are rarely discussed within the analyzed literature. The most common barrier for the successful development of decision support systems is the low availability of data and project cases. This gap could be filled by the increased use of BIM, which is fundamentally changing processes in the whole building lifecycle. In fact, BIM has already been successfully integrated within decision support systems for applications in the field of design and planning [42,53,54,95].

The results show that decision support systems can be successfully employed within every lifecycle phase of a building. The most addressed phase is the construction phase, where decision support systems aid decision making in different application areas that vary from supply chain management to optimization of logistics and decision problems related to scheduling problems. As applications

are mainly dedicated to decision problems for administrative and managerial activities, we see the ground for potential developments in the field of construction site operation Here, the predominance of MCDA methods is lower, and more methods that account for uncertainty are used. Furthermore, in the design and development phase, decision support systems are widely employed. Less applications are found for the operation and maintenance phase where applications are mainly dedicated to modernization measures of existing buildings. Within this phase, there is therefore still a lot of ground for developments.

5. Conclusions

Methods for decision support and applications of decision support systems in building construction are identified by performing a systematic literature review. Relevant literature is selected, screened, analyzed, and classified according to categories of methods and applications. This provides immediate information on the current use of methods and existing applications of decision support systems in the building lifecycle.

For every lifecycle phase, several applications of decision support systems exist, with the most addressed phase being the construction phase. Methods for decision support present substantial differences in terms of needed input and provided output. The selection of the most suitable method for decision making in building construction is a crucial task in the development of dedicated decision support systems. Within the selection, the boundary conditions and the nature of the decision problem must be considered. Handling of expert knowledge and scarce availability of data have emerged as a common limitation that authors of the most relevant existing works stress. This problem could be overcome by the increasing adoption of BIM in the construction sector. Further research in this field could account for the roles that different decision makers can have in the building lifecycle and on different types of delivery systems.

The results shed light on the most common and most effective methods and their use for decision support in building construction. The compact representation of the results provides information for the preliminary evaluation of the most suitable method for a specific decision problem. The findings of the review offer a basis for identifying the gap for future applications and show in which field we find still a lot of ground for new developments.

References

1. García, S.; Romero, O.; Raventós, R. DSS from an RE Perspective: A systematic mapping. *J. Syst. Softw.* **2016**, *117*, 488–507. [CrossRef]
2. Jato-Espino, D.; Castillo-Lopez, E.; Rodriguez-Hernandez, J.; Canteras-Jordana, J.C. A review of application of multi-criteria decision making methods in construction. *Autom. Constr.* **2014**, *45*, 151–162. [CrossRef]
3. Bakht, M.N.; El-Diraby, T.E. Synthesis of Decision-Making Research in Construction. *J. Constr. Eng. Manag.* **2015**, *141*, 04015027. [CrossRef]
4. Marcher, C.; Giusti, A.; Schimanski, C.P.; Matt, D.T. Application of Decision Support Systems for Advanced Equipment Selection in Construction. In *Cooperative Design, Visualization, and Engineering*; Lecture Notes in Computer Science; Luo, Y., Ed.; Springer International Publishing: Cham, Switzerland, 2019; Volume 11792, pp. 229–235. ISBN 978-3-030-30948-0.
5. Gorry, G.A.; Morton, M.S. A framework for management information systems. *Sloan Manag. Rev.* **1989**, *30*, 49–61.
6. Power, D.J. *Decision Support Systems: Concepts and Resources for Managers*; Greenwood Publishing Group: Westport, CT, USA, 2002; ISBN 1-56720-497-X.

7. Antucheviciene, J.; Kala, Z.; Marzouk, M.; Vaidogas, E.R. Decision Making Methods and Applications in Civil Engineering. *Math. Probl. Eng.* **2015**, *2015*, 1–3. [CrossRef]

8. Navarro, I.J.; Yepes, V.; Martí, J.V. A Review of Multicriteria Assessment Techniques Applied to Sustainable Infrastructure Design. *Adv. Civ. Eng.* **2019**, *2019*, 1–16. [CrossRef]

9. Ross, T.J. *Fuzzy Logic with Engineering Applications*, 1st ed.; Wiley: Hoboken, NJ, USA, 2010; ISBN 978-0-470-74376-8.

10. Alpaydin, E. *Machine Learning: The New AI*; MIT Press: Cambridge, MA, USA, 2016; ISBN 0-262-52951-3.

11. Faul, A.C. *A Concise Introduction to Machine Learning*; Machine Learning & Pattern Recognition; Chapman & Hall/CRC: Boca Raton, FL, USA, 2020; ISBN 978-1-351-20475-0.

12. Holland, J.H. Genetic Algorithms. *Sci. Am.* **1992**, *267*, 66–73. [CrossRef]

13. Forbes, N. *Imitation of Life: How Biology Is Inspiring Computing*; The MIT Press: Cambridge, MA, USA, 2005; ISBN 978-0-262-25615-5.

14. Russell, S.J.; Norvig, P.; Davis, E. *Artificial Intelligence: A Modern Approach*, 3rd ed.; Prentice Hall series in artificial intelligence; Prentice Hall: Upper Saddle River, NJ, USA, 2010; ISBN 978-0-13-604259-4.

15. Denyer, D.; Tranfield, D. Producing a systematic review. In *The Sage Handbook of Organizational Research Methods*; Sage Publications Ltd.: Thousand Oaks, CA, USA, 2009; pp. 671–689. ISBN 978-1-4129-3118-2.

16. Tranfield, D.; Denyer, D.; Smart, P. Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. *Br. J. Manag.* **2003**, *14*, 207–222. [CrossRef]

17. Kitchenham, B. *Procedures for Performing Systematic Reviews*; Keele University: Keele, UK; Empirical Software Engineering National ICT Australia Ltd.: Sydney, Australia, 2004; p. 33.

18. Ishizaka, A.; Nemery, P. *Multi-Criteria Decision Analysis: Methods and Software*; Wiley: Chichester, UK, 2013; ISBN 978-1-118-64491-1.

19. Greco, S.; Figueira, J.R.; Ehrgott, M. *Multiple Criteria Decision Analysis: State of the Art Surveys*; International Series in Operations Research & Management Science; Springer: New York, NY, USA, 2016; Volume 233, ISBN 978-1-4939-3093-7.

20. Hodgett, R.E. Comparison of multi-criteria decision-making methods for equipment selection. *Int. J. Adv. Manuf. Technol.* **2016**, *85*, 1145–1157. [CrossRef]

21. Zadeh, L.A. Fuzzy sets. *Inf. Control* **1965**, *8*, 338–353. [CrossRef]

22. Kjærulff, U.B.; Madsen, A.L. *Bayesian Networks and Influence Diagrams: A Guide to Construction and Analysis*; Information Science and Statistics; Springer: New York, NY, USA, 2013; Volume 22, ISBN 978-1-4614-5103-7.

23. Eastman, C.M.; Siabiris, A. A generic building product model incorporating building type information. *Autom. Constr.* **1995**, *3*, 283–304. [CrossRef]

24. Kamara, J.M. Integration in the project development process of a Private Finance Initiative (PFI) project. *Archit. Eng. Des. Manag.* **2012**, *8*, 228–245. [CrossRef]

25. Kamara, J. Exploring the Client–AEC Interface in Building Lifecycle Integration. *Buildings* **2013**, *3*, 462–481. [CrossRef]

26. Rempling, R.; Kurul, E.; Oti, A.H. *Research Roadmap for Information Integration in Construction*; Serial title 417; CIB General Secretariat: Delft, The Netherlands, 2019; ISBN 978-90-6363-09-66.

27. Royal Institute of British Architects. RIBA Plan of Work. 2020. Available online: https://www.architecture.com/knowledge-and-resources/resources-landing-page/riba-plan-of-work (accessed on 8 September 2020).

28. Daget, Y.T.; Zhang, H. Decision-making model for the evaluation of industrialized housing systems in Ethiopia. *Eng. Constr. Arch. Manag.* **2019**, *27*, 296–320. [CrossRef]

29. Zhong, Q.; Karner, A.; Kuby, M.; Golub, A. A multiobjective optimization model for locating affordable housing investments while maximizing accessibility to jobs by public transportation. *Environ. Plan.* **2019**, *46*, 490–510. [CrossRef]

30. Sharafi, P.; Rashidi, M.; Samali, B.; Ronagh, H.; Mortazavi, M. Identification of Factors and Decision Analysis of the Level of Modularization in Building Construction. *J. Arch. Eng.* **2018**, *24*, 04018010. [CrossRef]

31. De Azevedo, R.C.; De Oliveira Lacerda, R.T.; Ensslin, L.; Jungles, A.E.; Ensslin, S.R. Performance measurement to aid decision making in the budgeting process for apartment-building construction: Case study using MCDA-C. *J. Constr. Eng. Manag.* **2013**, *139*, 225–235. [CrossRef]

32. Stephen Okunlola, O.J.O. PROMA-A decision support system to determine appropriate procurement method. *Res. J. Appl. Sci. Eng. Technol.* **2012**, *4*, 316–321.

33. Chen, Y.; Okudan, G.E.; Riley, D.R. Decision support for construction method selection in concrete buildings: Prefabrication adoption and optimization. *Autom. Constr.* **2010**, *19*, 665–675. [CrossRef]

34. Chen, X.; Lu, W.; Xue, F.; Xu, J. A cost-benefit analysis of green buildings with respect to construction waste minimization using big data in Hong Kong. *J. Green Build.* **2018**, *13*, 61–76. [CrossRef]

35. Wang, Y.; Zou, Z. Spatial decision support system for urban planning: Case study of Harbin City in China. *J. Urban Plan. Dev.* **2010**, *136*, 147–153. [CrossRef]

36. Yusuf, S.A.; Georgakis, P.; Nwagboso, C. Procedural lot generation for evolutionary urban layout optimization in urban regeneration decision support. *Electron. J. Inf. Technol. Constr.* **2011**, *16*, 357–380.

37. Fallahpour, A.; Wong, K.Y.; Rajoo, S.; Olugu, E.U.; Nilashi, M.; Turskis, Z. A fuzzy decision support system for sustainable construction project selection: An integrated fpp-fis model. *J. Civ. Eng. Manag.* **2020**, *26*, 247–258. [CrossRef]

38. Hyung, W.-G.; Kim, S.; Jo, J.-K. Improved similarity measure in case-based reasoning: A case study of construction cost estimation. *Eng. Constr. Arch. Manag.* **2019**, *27*, 561–578. [CrossRef]

39. Hassim, S.; Muniandy, R.; Alias, A.H.; Abdullah, P. Construction tender price estimation standardization (TPES) in Malaysia: Modeling using fuzzy neural network. *Eng. Constr. Arch. Manag.* **2018**, *25*, 443–457. [CrossRef]

40. Chou, J.-S.; Cheng, M.-Y.; Wu, Y.-W.; Pham, A.-D. Optimizing parameters of support vector machine using fast messy genetic algorithm for dispute classification. *Expert Syst. Appl.* **2014**, *41*, 3955–3964. [CrossRef]

41. Akbari, S.; Khanzadi, M.; Gholamian, M.R. Building a rough sets-based prediction model for classifying large-scale construction projects based on sustainable success index. *Eng. Constr. Arch. Manag.* **2018**, *25*, 534–558. [CrossRef]

42. Kim, J.I.; Kim, J.; Fischer, M.; Orr, R. BIM-based decision-support method for master planning of sustainable large-scale developments. *Autom. Constr.* **2015**, *58*, 95–108. [CrossRef]

43. Hosny, O.; Nassar, K.; Olusola, P.A. Decision support system for housing developers in developing countries under uncertain buyer behavior. *J. Manag. Eng.* **2012**, *28*, 311–323. [CrossRef]

44. Košičan, J.; Pardo, M.Á.; Vilčeková, S. A multicriteria methodology to select the best installation of solar thermal power in a family house. *Energies* **2020**, *13*, 1047. [CrossRef]

45. Saleem, M.; Chhipi-Shrestha, G.; Túlio Barbosa Andrade, M.; Dyck, R.; Ruparathna, R.; Hewage, K.; Sadiq, R. Life Cycle Thinking-Based Selection of Building Facades. *J. Arch. Eng.* **2018**, *24*, 04018029. [CrossRef]

46. Rogulj, K.; Jajac, N. Achieving a Construction Barrier-Free Environment: Decision Support to Policy Selection. *J. Manag. Eng.* **2018**, *34*, 04018020. [CrossRef]

47. Arroyo, P.; Mourgues, C.; Flager, F.; Correa, M.G. A new method for applying choosing by advantages (CBA) multicriteria decision to a large number of design alternatives. *Energy Build.* **2018**, *167*, 30–37. [CrossRef]

48. Zavadskas, E.K.; Bausys, R.; Juodagalviene, B.; Garnyte-Sapranaviciene, I. Model for residential house element and material selection by neutrosophic MULTIMOORA method. *Eng. Appl. Artif. Intell.* **2017**, *64*, 315–324. [CrossRef]

49. Aviža, D.; Turskis, Z.; Kaklauskas, A. A Multiple criteria decision support system for analyzing the correlation between the thickness of a thermo-insulation layer and its payback period of the external wall. *J. Civ. Eng. Manag.* **2015**, *21*, 827–835. [CrossRef]

50. Bakhoum, E.S.; Brown, D.C. An automated decision support system for sustainable selection of structural materials. *Int. J. Sust. Eng.* **2015**, *8*, 80–92. [CrossRef]

51. Rahman, S.; Odeyinka, H.; Perera, S.; Bi, Y. Product-cost modelling approach for the development of a decision support system for optimal roofing material selection. *Expert Syst. Appl.* **2012**, *39*, 6857–6871. [CrossRef]

52. Fernandez-Ceniceros, J.; Fernandez-Martinez, R.; Fraile-Garcia, E.; Martinez-De-Pison, F.J. Decision support model for one-way floor slab design: A sustainable approach. *Autom. Constr.* **2013**, *35*, 460–470. [CrossRef]

53. Bianconi, F.; Filippucci, M.; Buffi, A. Automated design and modeling for mass-customized housing. A web-based design space catalog for timber structures. *Autom. Constr.* **2019**, *103*, 13–25. [CrossRef]

54. Chardon, S.; Brangeon, B.; Bozonnet, E.; Inard, C. Construction cost and energy performance of single family houses: From integrated design to automated optimization. *Autom. Constr.* **2016**, *70*, 1–13. [CrossRef]

55. Kripakaran, P.; Hall, B.; Gupta, A. A genetic algorithm for design of moment-resisting steel frames. *Struct. Mutltidiscip. Opt.* **2011**, *44*, 559–574. [CrossRef]

56. Forde, J.; Hopfe, C.J.; McLeod, R.S.; Evins, R. Temporal optimization for affordable and resilient Passivhaus dwellings in the social housing sector. *Appl. Energy* **2020**, *261*, 114383. [CrossRef]

57. Jeong, J.S.; Ramírez-Gómez, Á. Development of a web graphic model with fuzzy-decision-making Trial and Evaluation Laboratory/Multi-criteria-Spatial Decision Support System (F-DEMATEL/MC-SDSS) for sustainable planning and construction of rural housings. *J. Clean. Prod.* **2018**, *199*, 584–592. [CrossRef]

58. Singhaputtangkul, N. A decision support tool to mitigate decision-making problems faced by a building design team. *Smart Sustain. Built Environ.* **2017**, *6*, 2–18. [CrossRef]

59. Del Caño, A.; Pilar de la Cruz, M.; Gómez, D.; Pérez, M. Fuzzy method for analysing uncertainty in the sustainable design of concrete structures. *J. Civ. Eng. Manag.* **2016**, *22*, 924–935. [CrossRef]

60. Cheng, J.C.P.; Ma, L.J. A non-linear case-based reasoning approach for retrieval of similar cases and selection of target credits in LEED projects. *Build. Environ.* **2015**, *93*, 349–361. [CrossRef]

61. Ferreiro-Cabello, J.; Fraile-Garcia, E.; Martinez de Pison Ascacibar, E.; Martinez de Pison Ascacibar, F.J. Metamodel-based design optimization of structural one-way slabs based on deep learning neural networks to reduce environmental impact. *Eng. Struct.* **2018**, *155*, 91–101. [CrossRef]

62. Liu, K.-S.; Hsueh, S.-L.; Wu, W.-C.; Chen, Y.-L. A DFuzzy-DAHP decision-making model for evaluating energy-saving design strategies for residential buildings. *Energies* **2012**, *5*, 4462–4480. [CrossRef]

63. Del Caño, A.; Gómez, D.; De La Cruz, M.P. Uncertainty analysis in the sustainable design of concrete structures: A probabilistic method. *Constr. Build. Mater.* **2012**, *37*, 865–873. [CrossRef]

64. Park, S.-C.; Koo, K.-J. CBR-genetic algorithm based design team selection model for large-scale design firms. *KSCE J. Civ. Eng.* **2011**, *15*, 1141–1148. [CrossRef]

65. Du, J.; Jing, H.; Castro-Lacouture, D.; Sugumaran, V. Multi-agent simulation for managing design changes in prefabricated construction projects. *Eng. Constr. Arch. Manag.* **2019**, *27*, 270–295. [CrossRef]

66. Lin, Y.-H.; Tsai, K.-T.; Lin, M.-D.; Yang, M.-D. Design optimization of office building envelope configurations for energy conservation. *Appl. Energy* **2016**, *171*, 336–346. [CrossRef]

67. Singhaputtangkul, N.; Low, S.P.; Teo, A.L.; Hwang, B.-G. Knowledge-based decision support system quality function deployment (KBDSS-QFD) tool for assessment of building envelopes. *Autom. Constr.* **2013**, *35*, 314–328. [CrossRef]

68. Anastaselos, D.; Oxizidis, S.; Papadopoulos, A.M. Energy, environmental and economic optimization of thermal insulation solutions by means of an integrated decision support system. *Energy Build.* **2011**, *43*, 686–694. [CrossRef]

69. Enshassi, M.S.A.; Walbridge, S.; West, J.S.; Haas, C.T. Probabilistic Risk Management Framework for Tolerance-Related Issues in Modularized Projects: Local and Global Perspectives. *Asce-Asme J. Risk Uncertain Eng. Syst. Part A Civ. Eng.* **2020**, *6*, 04019022. [CrossRef]

70. Kannimuthu, M.; Raphael, B.; Ekambaram, P.; Kuppuswamy, A. Comparing optimization modeling approaches for the multi-mode resource-constrained multi-project scheduling problem. *Eng. Constr. Arch. Manag.* **2019**, *27*, 893–916. [CrossRef]

71. Ahmed, M.; Qureshi, M.N.; Mallick, J.; Ben Kahla, N. Selection of Sustainable Supplementary Concrete Materials Using OSM-AHP-TOPSIS Approach. *Adv. Mater. Sci. Eng.* **2019**, *2019*, 2850480. [CrossRef]

72. Duchaczek, A.; Skorupka, D. The Optimisation of the Selection of Means of Transport for the Implementation of Chosen Construction Projects. *KSCE J. Civ. Eng.* **2018**, *22*, 3633–3643. [CrossRef]

73. Chisala, M.L. Quantitative Bid or No-Bid Decision-Support Model for Contractors. *J. Constr. Eng. Manag.* **2017**, *143*, 04017088. [CrossRef]

74. Semaan, N.; Salem, M. A deterministic contractor selection decision support system for competitive bidding. *Eng. Constr. Arch. Manag.* **2017**, *24*, 61–77. [CrossRef]

75. Eshtehardian, E.; Ghodousi, P.; Bejanpour, A. Using ANP and AHP for the supplier selection in the construction and civil engineering companies; Case study of Iranian company. *KSCE J. Civ. Eng.* **2013**, *17*, 262–270. [CrossRef]

76. Chao, L.-C. Estimating project overheads rate in bidding: DSS approach using neural networks. *Constr. Manag. Econ.* **2010**, *28*, 287–299. [CrossRef]

77. Utama, W.P.; Chan, A.P.C.; Zahoor, H.; Gao, R.; Jumas, D.Y. Making decision toward overseas construction projects: An application based on adaptive neuro fuzzy system. *Eng. Constr. Arch. Manag.* **2019**, *26*, 285–302. [CrossRef]

78. Efe, B.; Kurt, M. A novel approach recommendation for hazard analysis. *Int. J. Occup. Saf. Erg.* **2019**, in press. [CrossRef]

79. Gunduz, M.; Nielsen, Y.; Ozdemir, M. Fuzzy assessment model to estimate the probability of delay in Turkish construction projects. *J. Manag. Eng.* **2015**, *31*, 4014055. [CrossRef]

80. Enshassi, M.S.A.; Walbridge, S.; West, J.S.; Haas, C.T. Dynamic and Proactive Risk-Based Methodology for Managing Excessive Geometric Variability Issues in Modular Construction Projects Using Bayesian Theory. *J. Constr. Eng. Manag.* **2020**, *146*, 04019096. [CrossRef]

81. Son, P.V.H. Reasoned bargaining protocol in construction contracts using a novel Bayesian game. *Int. J. Comput. Appl. Technol.* **2020**, *62*, 148–157. [CrossRef]

82. Wu, L.; Ji, W.; Abourizk, S.M. Bayesian Inference with Markov Chain Monte Carlo-Based Numerical Approach for Input Model Updating. *J. Comput. Civ. Eng.* **2020**, *34*, 04019043. [CrossRef]

83. Dutta, S.; Cai, Y.; Huang, L.; Zheng, J. Automatic re-planning of lifting paths for robotized tower cranes in dynamic BIM environments. *Autom. Constr.* **2020**, *110*, 102998. [CrossRef]

84. Hammad, A.W.; Akbarnezhad, A.; Wu, P.; Wang, X.; Haddad, A. Building information modelling-based framework to contrast conventional and modular construction methods through selected sustainability factors. *J. Clean. Prod.* **2019**, *228*, 1264–1281. [CrossRef]

85. Marzoughi, F.; Arthanari, T.; Askarany, D. A decision support framework for estimating project duration under the impact of weather. *Autom. Constr.* **2018**, *87*, 287–296. [CrossRef]

86. Sahu, A.K.; Sahu, N.K.; Sahu, A.K. Knowledge based decision support system for appraisement of sustainable partner under fuzzy cum non-fuzzy information. *Kybernetes* **2018**, *47*, 1090–1121. [CrossRef]

87. Wang, Y.; Feng, K.; Lu, W. An environmental assessment and optimization method for contractors. *J. Clean. Prod.* **2017**, *142*, 1877–1891. [CrossRef]

88. Nursal, A.T.; Omar, M.F.; Nawi, M.N.M.; Asri, M.A.N.M. Adoption of cloud based decision support system for building information modeling software selection. *Adv. Sci. Lett.* **2016**, *22*, 1310–1313. [CrossRef]

89. Marzouk, M.; Abubakr, A. Decision support for tower crane selection with building information models and genetic algorithms. *Autom. Constr.* **2016**, *61*, 1–15. [CrossRef]

90. Leu, S.-S.; Hong Son, P.V.; Hong Nhung, P.T. Optimize negotiation price in construction procurement using Bayesian Fuzzy Game Model. *KSCE J. Civ. Eng.* **2015**, *19*, 1566–1572. [CrossRef]

91. Leu, S.-S.; Pham, V.H.S.; Pham, T.H.N. Development of recursive decision making model in bilateral construction procurement negotiation. *Autom. Constr.* **2015**, *53*, 131–140. [CrossRef]

92. Chen, W.T.; Chang, P.-Y.; Chou, K.; Mortis, L.E. Developing a CBR-based adjudication system for fatal construction industry occupational accidents. Part I: Building the system framework. *Expert Sys. Appl.* **2010**, *37*, 4867–4880. [CrossRef]

93. Tang, L.C.M.; Leung, A.Y.T.; Wong, C.W.Y. Entropic risk analysis by a high level decision support system for construction SMEs. *J. Comput. Civ. Eng.* **2010**, *24*, 81–94. [CrossRef]

94. Chen, P.-H.; Nguyen, T.C. A BIM-WMS integrated decision support tool for supply chain management in construction. *Autom. Constr.* **2019**, *98*, 289–301. [CrossRef]

95. Kim, K.; Cho, Y.; Kim, K. BIM-Driven Automated Decision Support System for Safety Planning of Temporary Structures. *J. Constr. Eng. Manag.* **2018**, *144*, 04018072. [CrossRef]

96. Hsu, P.-Y.; Angeloudis, P.; Aurisicchio, M. Optimal logistics planning for modular construction using two-stage stochastic programming. *Autom. Constr.* **2018**, *94*, 47–61. [CrossRef]

97. Kog, F.; Yaman, H. A multi-agent systems-based contractor pre-qualification model. *Eng. Constr. Arch. Manag.* **2016**, *23*, 709–726. [CrossRef]

98. Goh, Y.M.; Guo, B.H.W. FPSWizard: A web-based CBR-RBR system for supporting the design of active fall protection systems. *Autom. Constr.* **2018**, *85*, 40–50. [CrossRef]

99. Zavichi, A.; Madani, K.; Xanthopoulos, P.; Oloufa, A.A. Enhanced crane operations in construction using service request optimization. *Autom. Constr.* **2014**, *47*, 69–77. [CrossRef]

100. Tahsildoost, M.; Zomorodian, Z. Energy, carbon, and cost analysis of rural housing retrofit in different climates. *J. Build. Eng.* **2020**, *30*, 101277. [CrossRef]

101. Andersen, S.C.; Møller, K.L.; Jørgensen, S.W.; Jensen, L.B.; Birkved, M. Scalable and quantitative decision support for the initial building design stages of refurbishment. *J. Green Build.* **2019**, *14*, 35–56. [CrossRef]

102. Seddiki, M.; Anouche, K.; Bennadji, A.; Boateng, P. A multi-criteria group decision-making method for the thermal renovation of masonry buildings: The case of Algeria. *Energy Build.* **2016**, *129*, 471–483. [CrossRef]

103. Rasiulis, R.; Ustinovichius, L.; Vilutiene, T.; Popov, V. Decision model for selection of modernization measures: Public building case. *J. Civ. Eng. Manag.* **2016**, *22*, 124–133. [CrossRef]

104. Kanapeckiene, L.; Kaklauskas, A.; Zavadskas, E.K.; Raslanas, S. Method and system for Multi-Attribute Market Value Assessment in analysis of construction and retrofit projects. *Expert Sys. Appl.* **2011**, *38*, 14196–14207. [CrossRef]

105. Mishra, M.; Bhatia, A.S.; Maity, D. Predicting the compressive strength of unreinforced brick masonry using machine learning techniques validated on a case study of a museum through nondestructive testing. *J. Civ. Struct. Health Monit.* **2020**, *10*, 389–403. [CrossRef]

106. Kabak, M.; Köse, E.; Kirilmaz, O.; Burmaoğlu, S. A fuzzy multi-criteria decision making approach to assess building energy performance. *Energy Build.* **2014**, *72*, 382–389. [CrossRef]

107. Cho, K.; Kim, J.; Kim, T. Decision support method for estimating monetary value of post-renovation office buildings. *Can. J. Civ. Eng.* **2019**, *46*, 1103–1113. [CrossRef]

108. Guardigli, L.; Bragadin, M.A.; Della Fornace, F.; Mazzoli, C.; Prati, D. Energy retrofit alternatives and cost-optimal analysis for large public housing stocks. *Energy Build.* **2018**, *166*, 48–59. [CrossRef]

109. Aguacil, S.; Lufkin, S.; Rey, E.; Cuchi, A. Application of the cost-optimal methodology to urban renewal projects at the territorial scale based on statistical data—A case study in Spain. *Energy Build.* **2017**, *144*, 42–60. [CrossRef]

110. Omar, M.F.; Nursal, A.T.; Nawi, M.N.M.; Haron, A.T.; Goh, K.C. A preliminary requirement of decision support system for Building Information Modelling software selection. *Malays. Constr. Res. J.* **2014**, *15*, 11–28.

111. Kanapeckiene, L.; Kaklauskas, A.; Zavadskas, E.K.; Seniut, M. Integrated knowledge management model and system for construction projects. *Eng. Appl. Artif. Intell.* **2010**, *23*, 1200–1215. [CrossRef]

112. Mahfouz, T.; Kandil, A.; Davlyatov, S. Identification of latent legal knowledge in differing site condition (DSC) litigations. *Autom. Constr.* **2018**, *94*, 104–111. [CrossRef]

113. Akcay, C.; Manisali, E. Fuzzy decision support model for the selection of contractor in construction works. *Rev. Constr.* **2018**, *17*, 258–266. [CrossRef]

114. Hamidreza, A.N.; Golabchi, M.; Saghatforoush, E. Development of new evaluation methods for qualitative alternatives, using fuzzy calculations. *Eur. J. Sci. Res.* **2011**, *51*, 305–314.

115. Cho, K.; Hastak, M. Time and cost-optimized decision support model for fast-track projects. *J. Constr. Eng. Manag.* **2013**, *139*, 90–101. [CrossRef]

116. Hosny, O.; Nassar, K.; Esmail, Y. Prequalification of Egyptian construction contractors using fuzzy-AHP models. *Eng. Constr. Arch. Manag.* **2013**, *20*, 381–405. [CrossRef]

117. Kassab, M.; Hegazy, T.; Hipel, K. Computerized DSS for construction conflict resolution under uncertainty. *J. Constr. Eng. Manag.* **2010**, *136*, 1249–1257. [CrossRef]

118. Abuwarda, Z.; Hegazy, T. Work-Package Planning and Schedule Optimization for Projects with Evolving Constraints. *J. Comput. Civ. Eng.* **2016**, *30*, 04016022. [CrossRef]

119. Menesi, W.; Hegazy, T. Multimode resource-constrained scheduling and leveling for practical-size projects. *J. Manag. Eng.* **2015**, *31*, 04014092. [CrossRef]

120. Hegazy, T.; Menesi, W. Enhancing the critical path segments scheduling technique for project control. *Can. J. Civ. Eng.* **2012**, *39*, 968–977. [CrossRef]

121. Zhang, Y.; Ng, S.T. An ant colony system based decision support system for construction time-cost optimization. *J. Civ. Eng. Manag.* **2012**, *18*, 580–589. [CrossRef]