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Contractor Selection for Construction Projects Using Consensus Tools and Big Data

Osman Taylan[1] · Muhammed R. Kabli[1] · Carlos Porcel[2] · Enrique Herrera-Viedma[3,4]

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Abstract Completing construction projects in time requires highly integrated contractor selection processes. Selecting the 'best' contractor is a multi-criteria and multi-group hard decision-making problem. The decision makers (DMs) usually do not have a joint interest in achieving agreement on choosing the best contractor. Traditionally, consensus on a decision does not mean a full and unanimous agreement on the selection criteria. Because the criteria expressed by quantitative and/or qualitative data are generally conflicting, an improvement in one often results in declining the others. Therefore, DMs base their judgments upon huge-size, high-variety and conflicting data which refer to Big Data. Hence, massive amount of data are analyzed in an iterative and time-sensitive manner for the crucial success of organizations. This study aims to integrate the contractor selection approaches for the formulation of decision problems using fuzzy and crisp data. Fuzzy AHP approach was employed for determining the criteria weights, and fuzzy TOPSIS method was used to find out the performance of contractors. Fuzzy extension of AHP enables the pair-wise comparison of criteria using synthetic global scores based on the data of a single expert. However, in this study, we used the data of multiple DMs and averaged the aggregated findings in the pair-wise comparison table; hence, seven contractors were evaluated based on the Big Data. The results showed that these methodologies are able to assess contractors' Big Data in a more scientific and practical way. The suggested approach helped to select the best contractor or share the projects between equally strong contractors.

Keywords Contractor · Fuzzy AHP · Fuzzy TOPSIS · Big Data

1 Introduction

Group decision making aims to solve problems that have a number of possible alternatives, in which a set of DMs deliver their preferences about the criteria and sub-criteria [1–3]. In such decision situations, the use of fuzzy tools is very popular in order to manage the uncertainties in the decision-making problems by providing different tools of preferences to build decision support systems [4–8]. On the other hand, the DMs will not have unique objectives and motivations and thus the decision process should be approached from various perspectives. It is unusual that the DMs have mutual interest in achieving agreement on choosing the best alternative. In practice, group decision making only allows differentiating between two states, namely the absence and existence of consensus [9, 10]. Consensus is a general agreement and the opinion of most of the DMs which is not a full and unanimous agreement. It can be stated that if some DMs are not willing to fully agree and also fully change their opinions on a case, the consensus can be reached by incorporating with the project

✉ Osman Taylan
otaylan@kau.edu.sa

1 Department of Industrial Engineering, Faculty of Engineering, King Abdulaziz University, P.O. Box 80204, Jeddah, Saudi Arabia

2 Department of Computer Science, University of Jaén, Jaén, Spain

3 Department of Electrical and Computer Engineering, Faculty of Engineering, King Abdulaziz University, P.O. Box 80204, Jeddah, Saudi Arabia

4 Department of Computer Science and Artificial Intelligence, University of Granada, Granada, Spain

manager (PM). In such cases, the PM could address the consensus reaching process (CRP) and then the consensus aims at attaining the consent, not necessarily the agreement of all DMs. These decisions accommodate the views of all parties involved to accomplish a decision. Such decisions will be beneficial to the whole decision-making group, not necessarily to the particular DMs who may give consent, however not necessarily for their first choice. On the other hand, a full consent does not mean that each DM is in full agreement for the solution of a case. DMs are only agreed to what someone wishes. It is not possible to freeze the past decisions made (by Expert systems or machine learning algorithms) in the form of rules taken by humans applied during new executions of some business processes (BPs) without the intervention of human judgment [4, 11]. For a CRP, there are a great number of non-cooperative manners and criteria-related data, because some actors usually state their ideas dishonestly or reject to amend their opinions to further their own interests. Hence, some novel consensus frameworks were suggested by Dong et al. [12] for managing non-cooperative behaviors. In their proposed framework, in order to generate numerical weights, a self-management mechanism is presented and integrated into the CRP. A drawback for the above-mentioned approaches is that there are no criteria that determine always the optimal decisions since context and matter of decision may differ from situation to situation; on the other hand, there are significant challenges related to the complexities of data integration [13, 14], synchronization of large data [15], lack of availability of skilled experts [16], and data security and privacy problems [17] to make decision. The adoption of Big Data technologies has mitigated numerous issues related to the processing and storage of large amount of data and images for decision making. However, there is still a lack of systems and methodologies that provide an intuitive analysis mechanism of heterogeneous dataset in the case of a very large number of DMs and criteria. Moreover, data processing for decision making not only requires defining links between images, data dictionaries and metadata associated with different means, but also enables DMs to conduct analyses in a more user-friendly way. These drawbacks can be stated that no solid criteria are available to determine the optimal decision, since context, matter of discussion, and the decision-making actors involved may differ at each attempt of execution. Therefore, in construction companies, large amount of data is accumulated which may frustrate to achieve a consensus and establish a correct decision. Moreover, intelligent systems with automatic rules replaceable to human decision makers are not always applicable, and consequently such approaches cannot be generalized and scaled to different and heterogeneous situations.

A contractor plays crucial role in the completion of a construction project. Selection of the best contractor constitutes a key decision process for public and private organizations which is carried out by considering a set of criteria and utilized procedure accepted worldwide. A growing number of contractor selection techniques [18]. 2016) have been reflecting a rising recognition for the construction industry to improve its procurement process [19]. Han et al. [20] investigated important changes through various analyses to determine the common strategies for leading the selection of global contractors. The criteria sets involve the essential factors and related data in contractor selection problem for determining the ability of competent firms [21] as well as their degree of financial situation, technical capability, financial strength. For instance, Mohamed et al. [22] proposed a method for contractor selection to identify the risk of lowest cost biding approach commonly used among contractors. Several techniques have been studied to establish the contractor selection strategies. Soeini and Allahbakhshi [23] sought to identify the ways for reviewing and evaluating the contractors. They have determined three methods, namely statistical methods, fuzzy logic and business intelligence to evaluate the contractors. Cheng and Li [24] proposed a viable method used to cluster the strongest competitive environment for contractor selection at the worldwide level. Mohemad et al. [25] reviewed the current practices of Decision Support Systems (DSS) in construction tendering processes. Similarly, Kashiwhgi and Byfield [26] studied multi-attribute method using data envelopment analysis for contractor selection. The traditional DSS lack of capability to match the dynamics of criteria and ill-defined fuzzy linguistic data. The existing DSS tools in construction tendering processes are focused on usually quantitative data processing where the systems specifically analyze numerical values. On the other hand, the quantitative system could not directly search the exact problem structure from text. According to [19, 25], current challenges in decision making require comprehensive analysis of large volumes of both structured and unstructured data. Meanwhile, the data mining approaches have been integrated with DSS model to control and analyze the cost of a project in order to determine project performances, predict trends and support in decision making. The biggest challenge is to automate the analysis of all criteria using computerized tools. It is extremely hard to automatically convert unstructured data into structured data format for input criteria in decision-making processes. The current trend is toward a framework of using ontological-based extractions (fuzzy-based linguistic terms) for DSS in order to improve tender assessment process. The fuzzy-based linguistic terms (ontology) will open a gate for rule-based fuzzy systems for supporting decision-making processes.

Similarly, Juan [27] and Wong [28] suggested hybrid decision-making approaches for contactor selection using fuzzy set theory. Zhang [29] studied the hesitant fuzzy multi-criteria GDM with unknown weight information. Topcu [30] studied the contractor selection problem by applying the analytical hierarchy process (AHP) approaches. Jaskowski et al. [31] determined the advantages and disadvantages of criteria weight by standard AHP, fuzzy AHP and other related methods. They proposed the application of extended fuzzy AHP approach to the group decision-making problems. Their findings presented that the suggested fuzzy AHP method is superior to the traditional AHP in terms of the quality decision and data processing. Zavadskas et al. [32] proposed different multi-criteria decision techniques (MCDM) for contractor selection which are vital part of the project management, risk assessment of contractors [33] and risk management [21]. A MCDM approach is an evaluation and rewarding methodology to consider not only the cost, but also important criteria, sub-criteria and related dataset.

Dataset appears to be massive in decision making today and will almost surely appear small in the near future depending on the size of IT technologies, and hence the concept of big is problematic to locate exactly. However, the potential of Big Data is evident as it is counted as Top 10 Strategic Technology Trends for 2013 [34] and Top 10 Critical Technology Trends for the coming years. In essence, Big Data is the collective intelligence generated by individual person as well as a group of experts shared mainly through the technological environment, where everything can be processed, documented, calculated, digitally organized and transformed into knowledge or even meta-knowledge. It is a fact that organizational systems are locking the use of their Big Data for decision making. Big Data and their assessment often require merging multiple criteria and ideas of actors (DMs) from different disciplines and from diverse practices to investigate the relationships between data types that have not yet been explored. Normally, each activity is performed by different experts with different capabilities and skills. The main challenges faced and tackled during the implementation of these systems are related to very large datasets sizes, in different formats, and structures.

In this study, a thorough investigation was conducted to identify the key criteria of contractor selection. A survey was carried out in the Kingdom which aims to determine the criteria and related datasets; the first part of survey was for screening the pre-qualification criteria, the second part determined the main criteria for post-qualification, and the last part was for the assessment of data about contractor. Hence, the key criteria identified are 'financial situation of contractor,' 'technical ability of contractor,' 'management capability,' 'health and safety and the reputation of contractor.' Figure 1 shows the criteria and the sub-criteria determined for decision-making process. The approach presented in this study facilitates initially defining the criteria weights by aggregating the decision makers' judgments using fuzzy and crisp data. The aim of this study is to focus on establishing consensus on joint human (group) decision-making activities in construction business environment. The heterogeneous decision makers have to achieve a consensus to choose the most promising option to follow. As it is well known, no criteria available can always determine the best decisions, because in BPs, the context and argument of decision might be different from situation to situation. Thus, it is very important to examine the specifications of approaches and data supporting the human decision making, which are capable of taking into account the context in which processes run. As a rule of thumb, in business process (BP), it makes more sense to argue and measure the distance from a degree of consensus. As aforementioned, fuzzy set theory has delivered linguistic data [4, 6–8] for the analysis of such imprecise phenomena like consensus in construction management. The existence of uncertainty is a common characteristic of such phenomena that describes a wide range of real problems related to decision-making process. For example, if a group of DMs have to decide about the credit and financial strength, management capability or reputation of a contractor company using the imprecise fuzzy or numerical data, the uncertainty rises, hence the assessment tools not necessarily the quantitative but the qualitative tools may help to make a decision. For this reason, the fuzzy linguistic approximations came into existence as an approach which permit to suitably process the Big Data. In this respect, the contractor evaluation process is considered as a MCDM problem and a wide range of necessary and sufficient conditions must be evaluated to assess the contractors' capabilities in Saudi Arabia. Fuzzy AHP and fuzzy TOPSIS methodologies were integrated to solve the contractor selection problem using Big Data. This is due to the fact that the majority of decision makers prefer qualitative assessment tools due to either their ability to solve complex problems and inter-relatedness of the criteria or supporting the ways of conducting the necessary action for the large data. As a hybrid method, integrated fuzzy AHP and fuzzy TOPSIS methods are promising method for these sort of problems, which require handling complicated and highly interrelated data [35].

The rest of the paper is organized as follows: the criteria determination-related datasets, absence and existence of consensus for the assessment of construction industry preceding the introduction of the fuzzy AHP and fuzzy TOPSIS. The materials and methods for contractor selection and the implementation of fuzzy AHP for criteria weighting are presented in Sect. 2. Section 3 provides the

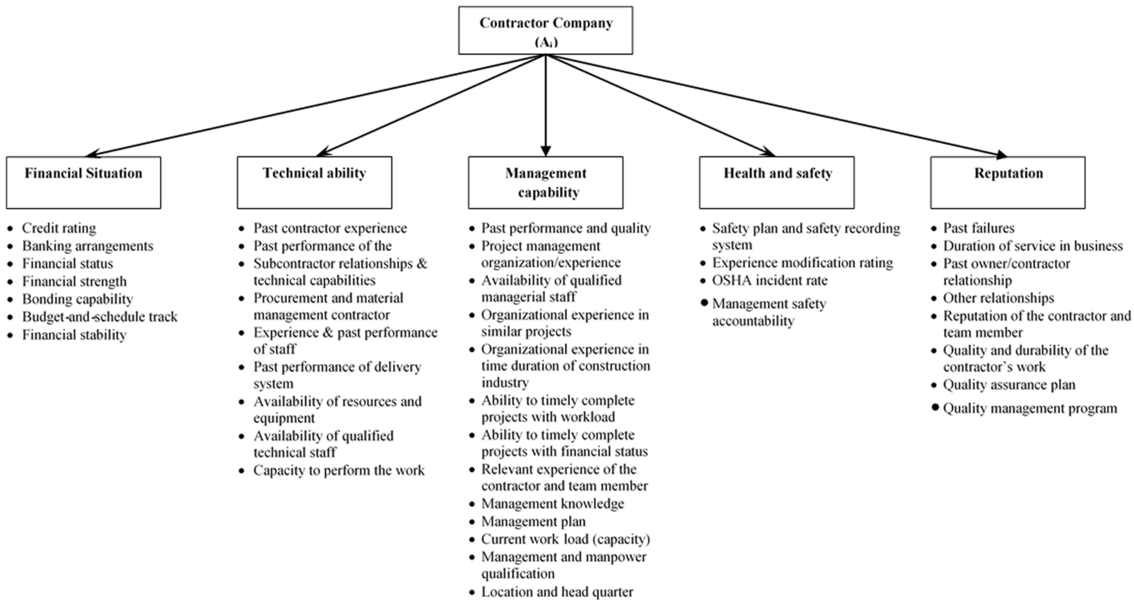

Fig. 1 A fuzzy decision tree for the combination of sub-criteria by different operators

detailed implementation of fuzzy TOPSIS methodology, and the discussions are presented in Sect. 4. After comparing the performance of the contractors, the paper culminates with the main conclusions in Sect. 5.

2 Materials and Methods for Contractor Selection

The research methodology selected for this study covers two steps including qualitative and quantitative approaches. Initially, a questionnaire was designed to reveal the main criteria and sub-criteria, and therefore interviews were carried out with qualified people in construction industry in Saudi Arabia. Contractor selection is a complete qualitative assessment of the main and sub-criteria. The information obtained from survey includes determining the contractor's sustained position in the business, suitability of tools and equipment to perform the work properly and the eligibility of financial situation of company to meet obligations required by the project. Similarly, determining the appropriate contractor(s) with technical ability and benchmarking the experience in similar projects regarding the size of contractor, the frequency of former failures might help to carry out contractor selection properly. The overall goal of contractor selection process is the reduction of construction project risk, maximizing the value to the project thoroughly, and building long-term relationships between members of the project.

In this study, two methods were integrated to determine the best contractors using Big Data. Initially, the weights of criteria were determined; a type of fuzzy aggregation approach with fuzzy AHP method was employed for criteria weight determination. The decision process includes two steps: firstly employing a group of DMs in order to ensure that the selection process used in this study is fair; hence, a team of five DMs were determined from a diverse decision-making group. The team includes a 'project manager, site engineer, site manager, design engineer, and an administrative staff,' to evaluate the contractors against five criteria. In the second step, the criteria set were identified which was the hardest part of this study. The best advice that can be suggested is to list all the potential criteria and prioritize them using the fuzzy linguistic terms, as it is categorized in Table 1. This is a multi-criteria, multi-DMs and multi-choice decision-making problem using Big Data, and hence the fuzzy preference relation approach based on consensus model can be used to solve the contractor selection problem. The method effectively discusses the drawback related to the AHP models. For instance, Singh et al. [36] evolved a fuzzy-based multi-criteria, multi-choice and multi-person decision-making heuristic problem to resolve the selection of lean tools.

Table 1 Fuzzy linguistic terms for defining the value of criteria

Extremely strong (ES)	(9,9,9)
Very strong (VS)	(7,8,9)
Strong (ST)	(6,7,8)
Moderately strong (MS)	(5,6,7)
Intermediate strong (IS)	(4,5,6)
Lower intermediate strong (LS)	(3,4,5)
Slightly more strong (SM)	(1,2,3)
Equally strong (ES)	(1,1,1)

They suggested a fuzzy AHP methodology to state the relative importance of criteria and data assured by different DMs, and these data are homogenized and multiplied by the weights allocated to the respective criteria.

The second approach covers the employment of fuzzy TOPSIS methodology for contractor selection in which neither the criteria are equally important nor are the related input data; on the other hand, the criteria-related data are not known precisely. TOPSIS methodology is one of an important approaches employed when one engaged in MCDM problems. It concurrently uses both the shortest distance from the positive-ideal solution (PIS) and the farthest distance from the negative-ideal solution (NIS). The order of preference is aligned based on their relative closeness by combining the measure of the two distances [37].

The objective of this study is to suggest an integrated method to ascertain the most eligible constructors for Saudi construction industry. Hence, let $A_i = \{a_1, a_2, \ldots, a_m\}$ represents a set of m alternative contractors, $U = \{u_1, u_2, \ldots, u_n\}$ represents a set of criteria (attributes), $D = \{d_1, d_2, \ldots, d_t\}$ represents the set of DMs, and let $M = \{1, 2, \ldots, m\}$ for $m \geq 2$, $N = \{1, 2, \ldots, n\}, (n \geq 2)$, and $T = \{1, 2, \ldots, t\}(t \geq 2); i \in M, j \in N,$ and $K \in T$.

$W = \{w_1, w_2, \ldots, w_n\}^T$ is the weight vector of attributes, where $w_j \geq 0, \sum_{j=1}^{n} w_j = 1; w_j \in [0, 1], j = 1, 2, \ldots, n, w_j^{(k)}$ is the given weight about jth attribute by DM k. On the other hand, $\varphi = (\varphi_1, \varphi_2, \ldots, \varphi_t)^T$ is the weight vector of DMs, where $\varphi_k \geq 0, \sum_{k=1}^{n} \varphi_k = 1, k = 1, 2, \ldots, t$. Now, let us suppose that $S = \{(s_i | i = -t, \ldots, -1,\ 0, 1, \ldots, t)\}$ is a finite and ordered discrete linguistic term set, where s_i is a the value for a linguistic variable, for instance, if S is a set of eight linguistic terms that can be used in this study; $S = \{s_1, s_2, \ldots s_7, s_8\}$. A multi-attribute group decision-making problem can be solved by a selection process, the solution is selected by a set of alternatives according to the opinion expressed by the DMs, without taking into account the consensus achieved within the group of DMs. Cabrerizo et al. [10] state that group decision making involves two steps: the first step is the aggregation which aims to attain a collective thought in which all the opinions are combined into only one preference. In this approach, each aims to reflect the properties contained in all the individual opinions. The second step is the e*xploitation, which aims* to obtain a partial order of the alternatives to select the best one(s) [38]. However, some DMs might not be agreed with the way of solving a group decision-making problem. In such cases, the DMs might refuse the decision made, because he/she might think that their ideas have not been considered conveniently to obtain the optimal solution. Therefore, Cabrerizo et al. [39] recommended that the DMs seek a consensus process in which their opinions gradually are discussed and changed to reach a conclusion before the selection process is applied. As a result, the consensus and selection process are employed before a final solution is obtained in a group decision-making situation [40].

As it appears in Fig. 1, five main criteria were considered. The criteria set is presented by $U = \{u_1, u_2, \ldots, u_n\}$ Hence, u_1 stands for *'financial situation of contractors,'* u_2 stands for *'technical ability of contractors,'* u_3 stands for *'management capability of contractors,'* u_4 stands for *'health and safety,'* and u_5 stands for *'reputation of contractors.'* To measure the degree of weights of each criteria, the linguistic terms and numeral given in Table 1 have been used. On the other hand, there are several subcriteria, fuzzy operators of fuzzy set theory were used to accumulate the decisions so that a more responsive aggregation model is established. The weight factors obtained from fuzzy AHP applications were normalized depending on the necessity of the decision problem. Figure 2 depicts the Big Data assessment procedure for decision making.

2.1 Fuzzy AHP Methodology for Determining the Contractor's Criteria Weights

Saaty [41] studied standard AHP method in many papers, which is an efficient approach to solve the MCDM problems. The aggregation of judgment was carried out to be geometric mean method in these studies. On the other

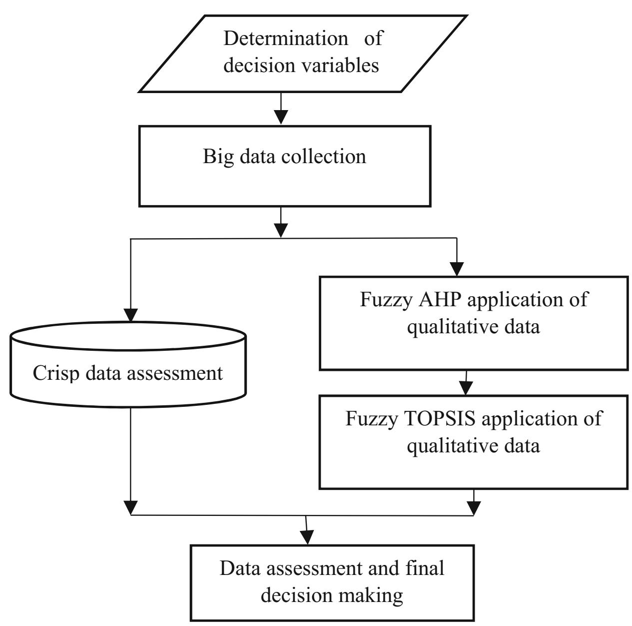

Fig. 2 Big Data assessment procedure for decision procedure

hand, Cho and Cho [42] suggested a new approach for group decision-making (GDM) problems considering the quality loss function approach in which the inconsistency ratio was used as the GDM and assessment tool. However, the DMs are not able to use AHP directly to process the incomplete data or solve the subjectivity of assessments. Fuzzy linear programming method was suggested by Mikhailov [43] to establish and determine the group priorities for maximizing through satisfaction with the crisp equations. Van Laarhoven and Pedrycz [44] and Chang [45] studied the extension of the AHP approach to determine the relative preferences with the aid of triangular fuzzy membership functions (TFFs). Fuzzy extension principle of AHP enables to compute the preferences depending on comparison of criteria data and synthetic scores to determine the weighted sum of criteria. However, in fuzzy extension of AHP, the pair-wise comparison is carried out based on the decision of a single decision maker. This is the deficiency of the approach. This study aims to consider multiple DMs (three decision makers) and use the average of aggregated decision in the pair-wise comparison table. The advantage of the approach is that the linguistic assessment of decision makers is used for the determination of the weights which are then used for fuzzy TOPSIS methodology to evaluate the contractors' superiority [46]. They employed Fuzzy AHP for fuzzy hierarchical analysis by describing the pair-wise comparisons using fuzzy numerical values. Chang's [45] extent analysis method is employed to determine the triangular fuzzy numbers. In Chang's [45] extent analysis, each and every criteria in the set is considered important simultaneously and the extension analysis is carried out, respectively. Similarly, Hensher and Stanley [47] worked out the client selection problem and chosen the contractors. Several surveys were carried out in which respondents were asked to rate the importance of specified criteria and sub-criteria directly and independently. The fuzzy linguistic terms employed in Table 1 were used for the aggregation of sub-criteria. As each activity is performed by different DMs with different capabilities and skills. Similarly, there is a large organizational body involved in data assessment and processing results of activities which can be labeled as the Big Data chain. The Big Data chains start with collecting the data from the sources and ends when data-based decisions are taken [48]. The term Big Data chain means the analytical view taken on the collaboration of criteria, DMs and assessors. Equation 1 was employed for averaging the decisions made for each pair-wise comparison of criteria where $\tilde{S}_{ij}$ is the comparison of ith criteria with jth criteria using numerical data presented in Table 1. $\tilde{S}_{ij} = \{\tilde{s}_{ij}\}_{nxm}$ is a fuzzy decision matrix of pair-wise comparison characterized by numerical data presented in Table 2. Equation 1 was employed for the aggregation and averaging of these decisions parameters. Three DMs were employed for the establishment of pair-wise comparison process. Hence, converting the selected datasets into machine readable data and adding metadata or knowledge can affect how Big Data can be employed for decision making.

$$\widetilde{S}_{ij} = \frac{1}{N}\left\{\widetilde{s}_{ij}^{(1)} + \widetilde{s}_{ij}^{(2)} + \cdots + \widetilde{s}_{ij}^{(N)}\right\} \tag{1}$$

Let us suppose M_{gi}^{j} ($j = 1, 2,\ldots,m$) are triangular fuzzy numbers (TFNs). $\sum_{j=1}^{m} M_{gi}^{j}$ can be calculated by addition operation of m extent analysis for a particular matrix. Hence, Eq. 2 shows the fuzzy numbers; 'c_j' depicts the maximum value, 'b_j' shows the average and 'a_j' shows the minimum value of fuzzy linguistic terms.

$$\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j=1}^{m} a_j, \sum_{j=1}^{m} b_j, \sum_{j=1}^{m} c_j\right). \tag{2}$$

The inverse of the numerical values can be calculated as it is presented in Eq. 3. 'S_{ui}' in this study, is an enforced Chang's [45] extent analysis method by adding the average decision of three DMs. Normally, in Chang's [45] extent approach, the decision of a single person is considered to establish the pair-wise comparison matrix. However, we have considered the decision of three persons. Hence, the fuzzy synthetic extent (S_{ui}) value related to the ith criteria is calculated by Eq. 3.

$$\begin{aligned} Su_i &= \sum_{j=1}^{m} M_{gi}^{j} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} = \tilde{W}_\imath \\ &= \{\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_n\}. \end{aligned} \tag{3}$$

The inverse of triangular numerical values is calculated as it is given in Eq. 4.

$$\left[\sum\nolimits_{i=1}^{n}\sum\nolimits_{j=1}^{m} M_{gi}^{i}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} c_i}, \frac{1}{\sum_{i=1}^{n} b_i}, \frac{1}{\sum_{i=1}^{n} a_i}\right) \tag{4}$$

let $V(M_2 \geq M_1) = \sup_{y \geq x}[\min(\mu_{M_1}(x), \mu_{M_2}(y))]$ shows the membership degree of two possible numerical values which can be presented as it is given in Eq. 4. For instance, if the linguistic variable is 'Technical ability' and its term set is characterized by {poor, fair, good, very good, excellent}. It can be characterized by its MFs. The pair-wise comparison matrix is constituted to designate the weight of criteria for the main attributes. Table 2 depicts the pair-wise comparison of all criteria set. The opinion of three DMs for each criteria was obtained, and the results are presented in this table. The 'technical ability' and 'management capability of contractor' are the attributes, and the application of the extension principles of fuzzy logic for these attributes is presented below, respectively.

Table 2 Fuzzy pair-wise comparison of construction project criteria

Fuzzy pair-wise decision matrix	u_1: Financial situation	u_2: Technical ability of contractors	u_3: Management capability	u_4: Health and safety	u_5: Reputation
u_1: Financial situation	(1, 1, 1)	(1/9, 1/9, 1/9)	(6, 7, 8)	(5, 6, 7)	(6, 7, 8)
u_2: Technical ability of contractors	(9, 9, 9)	(1, 1, 1)	(7, 8, 9)	(9, 9, 9)	(7, 8, 9)
u_3: Management capability	(1/8, 1/7, 1/6)	(1/9, 1/8, 1/7)	(1, 1, 1)	(1, 2, 3)	(1, 1, 1)
u_4: Health and safety	(1/7, 1/6, 1/5)	(1/9, 1/9, 1/9)	(1/3, 1/2, 1)	(1,1,1)	(1, 2, 3)
u_5: Reputation	(1/8, 1/7, 1/6)	(1/9, 1/8, 1/7)	(1,1,1)	(1/3, 1/2, 1)	(1, 1, 1)
Weights determined from pair-wise comparison	(18.11, 21.11, 24.11)	(33, 35, 37)	(3.31, 4.27, 5.24)	(3.31, 3.78, 4.59)	(3.31, 2.77, 2.57)

$$\sum_{j=2}^{5} M_1^5 = 9 + 1 + 7 + 9 + 7 = 33,$$

$$\sum_{j=2}^{5} M_2^5 = 9 + 1 + 8 + 9 + 8 = 35,$$

$$\sum_{j=2}^{5} M_3^5 = 9 + 1 + 9 + 9 + 9 = 37$$

$$\sum_{j=3}^{5} M_1^5 = 1/6 + 1/7 + 1 + 1 + 1 = 3.31,$$

$$\sum_{j=3}^{5} M_2^5 = 1/7 + 1/8 + 1 + 2 + 1 = 4.27,$$

$$\sum_{j=3}^{5} M_3^5 = 1/8 + 1/9 + 1 + 3 + 1 = 5.24$$

Equation 3 is used for the calculations of fuzzy synthetic extents *(Su_i)* in terms of all the main criteria. Initially, the inverse vector was calculated and then the result of (Su_1) for each criteria was calculated with details and presented below.

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} = [73.50, 66.92, 61.04]^{-1}$$
$$= [1/73.50, 1/66.92, 1/61.04]$$

$$Su_1 = \sum_{j=1}^{m} M_{gi}^{j} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1}$$
$$= (18.11, 21.11, 24.11 \otimes (1/73.50, 1/66.92, 1/61.04)$$
$$= (0.25, 0.32, 0.39)$$

The complete set of criteria with fuzzified values were determined and are presented in Table 3.

Table 3 Fuzzy weights of decision criteria

Fuzzy pair-wise decision matrix	Weights
u_1: Financial situation	(0.25, 0.32, 0.39)
u_2: Technical ability of contractors	(0.45, 0.52, 0.61)
u_3: Management capability of contractor	(0.05, 006, 0.09)
u_4: Health and safety	(0.05, 0.06, 0.08)
u_5: Reputation	(0.04, 0.05, 0.06)

2.2 Fuzzy TOPSIS Methodology for Decision Making Using Big Data

There are many steps for the Big Data processing in the literature [48] which starts with data capturing, storage, searching, sharing, analysis, visualization, problem definition, transformation, data entity resolution, and solving the problem for decision making. For instance, fuzzy TOPSIS approach uses subjective input data obtained from DMs to present the opinions about the contractors and solve the decision-making problem. The use of Big Data and data quality influences the decision-making quality. As data become larger, more complex and inexplicable, the limited mental capacities of DMs pose difficulties in explaining and interpreting the imprecise data environment. If the DMs have knowledge about the relationships among problem variables (decision criteria), the decision quality may improve. However, if the DMs do not have understood the relationships between the variables, the decision quality may degrade. On the other hand, the decision criteria (variables) are not equally important, and the input criteria-related data are not known precisely [49]. After the main criteria weights were determined by fuzzy AHP, each contractor was evaluated by fuzzy linguistic rates. Table 4 is employed to determine the importance of criteria and the rating of alternative contractors. Seven contractor companies applied for the construction projects and five large size construction projects were evaluated based on the pre-determined criteria, and hence there is a big dataset available. Due to the size of data available, the detailed calculations of one contractor company applied for a construction project will be presented in this study.

2.2.1 *The Fuzzy TOPSIS Procedure for Contractor Selection*

Step 1: The fuzzy weights are used, and the rates are determined in this step:

Table 4 Fuzzy terms and numerical values

Fuzzy linguistic terms for decision making	Fuzzy numerical values
Poor (P)	(1, 2, 3)
Fair (F)	(2, 3, 4)
Good (G)	(3, 4, 5)
Very good (VG)	(4, 5, 6)
Excellent (E)	(5, 7, 9)

Table 4 shows the fuzzy linguistic terms (T_i) used to identify the universe of discourse of the contractors' selection problem. In this study, the linguistic term set includes *{poor, fair, good, very good and excellent}* for rating the contractors. In fact, the fuzzy linguistic terms are imprecise and vague. The fuzzy term set (T_i) is the set of linguistic values identified by numerical data. The term set takes the numerical values between {1,…,9}. Let $\mu(s_i)$ is the set of membership functions and be $\mu(s_i) = \left\{\mu_{s_i}^{(1)}, \ldots, \mu_{s_i}^{(k_i)}\right\}$. $\mu(s_i)$ to relate each criteria or sub-criteria with its fuzzy equivalences. For instance, if s_1 refers to the 'financial situation' of the contractors which covers the sub-criteria set of 'credit rating, banking arrangements, financial status, financial strength, and bonding capability of the contractor,' then the term set of this linguistic criteria $T_{(i)}$ may be {poor, fair, good and/or excellent}. Now, let $N = \{n_1, n_2, \ldots, n_7\}$ be the set of contractor companies eligible to apply the construction project in the Saudi construction industry. Fuzzy numerical data were employed by the DMs to evaluate the contractor companies against each sub-criteria. The degree of each sub-criteria and main criteria was incorporated into the formulation using fuzzy numerical data and finding the rate of alternative contractor company. The eligible contractor company is obtained by multiplying the matrix of rate data with the vector of criteria weights data and summing the overall attributes. Hence, the calculation for rating of companies in terms of sub- and main criteria has been completed, and the details calculation for contractor #3 is presented in this study.

Step 2: Obtaining the normalized fuzzy decision matrix ($\tilde{R}_{ij}$).

There are various information/data sources and each of them appeared to be different, often providing the DMs a headache when they try to combine them. As it is well known, some criteria take numerical data some are identified only by linguistic data. The fuzzy membership degrees provide the conversion of linguistic data to numerical data of the contractors with regard to the main criteria. This process is presented by $\tilde{R}_{ij}$ in Eq. 5, in cases B and C are the sets of benefit criteria (see Eq. 6) and cost criteria (see Eq. 8), respectively. Then:

$$\tilde{R}_{ij} = [\tilde{r}_{ij}]_{m \times n} \tag{5}$$

$$c_j^* = \max_i c_{ij}, \quad \text{if} \quad j \in B; \tag{6}$$

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), \quad j \in B. \tag{7}$$

$$\begin{aligned} \tilde{r}_{ij} &= \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), \quad j \in C. \\ a_j^- &= \min_i a_{ij}, \quad \text{if } j \in C. \end{aligned} \tag{8}$$

Step 3: The weighted normalized fuzzy decision matrix is constructed using Eq. 9.

Decision making is more difficult when it is combined with other Big Data that may show a different pattern. The aim of normalization is to present the findings of linguistic terms in the range of triangular fuzzy numerical data. The weighted normalized fuzzy decision matrix can be constructed based on the importance of each criterion. The following multiplication can be employed to determine the weighted normalized fuzzy decision matrix.

$$\begin{aligned} \tilde{V}_{ij} &= \tilde{r}_{ij}(.)\tilde{w}_j \quad i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n \\ \tilde{V} &= [\tilde{v}_{ij}]_{m \times n}. \end{aligned} \tag{9}$$

3 The Results of Fuzzy TOPSIS Methodology for Contractor Selection

Determining the main criteria weights and calculating the rating of contractors, Table 4 can be established to show the importance of attributes and the ratings in terms of fuzzy linguistic terms. In this study, fuzzy numerical data were used to present the rating of main criteria and sub-criteria. The approach aims to average the decision of the kth DM for a contractor in terms of the sub-criteria by the fuzzy arithmetic summation function. This study shows only the detailed calculations for the data of 'financial situation' criteria of contractor #3. The calculations for the rest of data regarding the criteria were conducted in the same way, and the results are presented briefly.

3.1 The Determination of Fuzzy Numerical Values for Financial Situation of Contractor #3

Table 5 shows the fuzzy linguistic terms and the numerical data for financial situation of contractor #3. The involvement of a variety of criteria and chain of consecutive activities can be defined as the 'Big Data chain.' A Big Data chain consists of subsequent activities that can be distinguished analytically. The term 'chain' shows the analytical view taken on the collaboration of criteria. Hence, Eq. 1 is used to average the decisions of five DMs

Table 5 Fuzzy triangular numbers and linguistic terms for grading the contractor # 3 with respect to financial situation

C_1: Financial situation	DM_1	DM_2	DM_3	DM_4	DM_5	Average
Credit rating	VG, (4, 5, 6)	G, (3, 4, 5)	VG, (4, 5, 6)	F, (2, 3, 4)	F, (2, 3, 4)	(3, 4, 5)
Banking arrangements	G, (3, 4, 5)	E, (5, 7, 9)	G, (3, 4, 5)	VG, (4, 5, 6)	F, (2, 3, 4)	(3.4, 4.6, 5.8)
Financial status	G, (3, 4, 5)	E, (5, 7, 9)	F, (2, 3, 4)	VG, (4, 5, 6)	G, (3, 4, 5)	(3.4, 4.6, 5.8)
Financial strength	G, (3, 4, 5)	E, (5, 7, 9)	VG, (4, 5, 6)	VG, (4, 5, 6)	G, (3, 4, 5)	(3.8, 5, 6.2)
Bonding capability	F, (2, 3, 4)	E, (5, 7, 9)	F, (2, 3, 4)	F, (2, 3, 4)	G, (3, 4, 5)	(2.8, 4, 5.2)
Budget-and-schedule track	VG, (4, 5, 6)	VG, (4, 5, 6)	VG, (4, 5, 6)	VG, (4, 5, 6)	E, (5, 7, 9)	(4.2, 5.4, 6.6)
Financial stability	G, (3, 4, 5)	VG, (4, 5, 6)	VG, (4, 5, 6)	VG, (4, 5, 6)	VG, (4, 5, 6)	(3.4, 4.4, 5.4)

for each main and sub-criteria. The average of decision for all sub-criteria was calculated previously. The fuzzy linguistic terms used to define the sub-criteria 'credit rating,' are as follows: *{very good (VG), good (G), very good (VG), fair (F), fair (F)},* respectively.

The triangular numerical data were assigned to define the importance of sub-criteria, and fuzzy linguistic terms were used for the evaluation criteria. The linguistic term set for sub-criteria set of 'financial situation' is 'credit rating, banking arrangements, financial status, financial strength, and bonding capability' of the contractors. For instance, the DM #1 (DM1) has graded the contractor #3 for sub-criteria '*credit rating*' with (4, 5, 6) numerical data and '*financial stability*' with (3, 4, 5) in terms of the '*financial situation*' of the company (see Table 5). Similarly, the DM #5 graded the same sub-criteria with (2, 3, 4) numerical data and (4, 5, 6) for '*financial situation*' of the contractors, respectively. On the other hand, Table 5 also presents the average decision for contractor #3 which was made by five decision makers. A sample calculation of averaging the decision for contractor # 3 with regard to credit rating and financial strength is presented below, respectively.

$$u_{11}(\textit{credit rating}) = \frac{(4,5,6)+(3,4,5)+(4,5,6)+(2,3,4)+(2,3,4)}{5} = (3,4,5)$$

The average of numerical data rating made by decision makers for 'financial strength' is as follows;

$$u_{14}(\text{financial strength}) = \frac{(3,4,5)+(5,7,9)+(4,5,6)+(4,5,6)+(3,4,5)}{5} = (3.8,5,6.2)$$

Similar calculations were carried out for all contractors using fuzzy triangular numerical data and linguistic terms for grading the contractors in terms of all criteria and sub-criteria. The average of the decisions made was calculated in the similar way. The grand average of fuzzy numerical data with regard to all decision criteria for contractor #3 was calculated and is presented in Table 6.

3.2 The Fuzzy Decision Matrix for Contractor Selection

Step 2 presents the application of fuzzy TOPSIS methodology. The normalized fuzzy decision matrix was obtained by $\tilde{R}_{ij}$ which represents the fuzzy membership degree, in fact it is the strength of contractors with regards to the criteria. One advantage of fuzzy TOPSIS approach is to convert the crisp numerical findings to the fuzzy membership degrees. The aim is to show the importance of criteria and well define the linguistic concepts using the sensitivity of the aggregation to an individual membership data. The data in Table 7 are employed to determine c_j*, which refers the strongest contractors in terms of numerical data. The application of Eq. 6 showed that for instance c_1* is equal to 9.0 for the contractor #1, 8.56 for the second contractor, 5.71 for the third contractor and so on. The outcomes of calculations for some c_j* are presented below.

$$\text{Max}[(5.21,6.68,8.14),(7.80,8.40,9.0),(3.65,5.25,6.85), \times(5.52,6.50,7.48),(2.45,4.37,6.28)] = 9.0$$

$$\text{Max}[(4.70,6.31,7.92),(6.21,7.39,8.56),(1.36,2.96,4.56), \times(3.46,5.00,6.54),(5.84,6.90,7.96)] = 8.56$$

$$\text{Max}[(3.43,4.57,5.71),(3.16,4.22,5.29),(2.75,3.82,4.87), \times(2.25,3.25,4.25),(2.2,3.2,4.2)] = 5.71.$$

3.3 Fuzzification of the Numerical Values for the Selection of Contractors

Fuzzification is to identify the characteristics of a problem by fuzzy term sets and implications considering the state parameters. On the other hand, fuzzification means transforming non-fuzzy numerical (crisp) decision data into fuzzy equivalences in between [0, 1] by means of

Table 6 Grand average of fuzzy numerical values with regard to decision criteria for contractor #3

Criteria for contractor selection	The grand average of numerical values
u_1: Financial situation	(3.43, 4.57, 5.71)
u_2: Technical ability of contractors	(3.16, 4.22, 5.29)
u_3: Management capability of contractor	(2.75, 3.81, 4.88)
u_4: Health and safety	(2.25, 3.25, 4.25)
u_5: Reputation	(2.2, 3.2, 4.2)

Table 7 Numerical values determined for each contractor with respect to the criteria

Contractors	Criteria set				
	u_1	u_2	u_3	u_4	u_5
Contractor #1	(5.21, 6.68, 8.14)	(7.80, 8.40, 9.0)	(3.65, 5.25, 6.85)	(5.52, 6.50, 7.48)	(2.45, 4.37, 6.28)
Contractor #2	(4.70, 6.31, 7.92)	(6.21, 7.39, 8.56)	(1.36, 2.96, 4.56)	(3.46, 5.00, 6.54)	(5.84, 6.90, 7.96)
Contractor #3	(3.43, 4.57, 5.71)	(3.16, 4.22, 5.29)	(2.75, 3.82, 4.87)	(2.25, 3.25,4.25)	(2.2, 3.2, 4.2)
Contractor #4	(7.52, 8.09, 8.66)	(4.16, 5.29, 6.41)	(2.92, 3.74, 4.56)	(5.85, 6.75, 7.64)	(2.45, 2.85, 3.25)
Contractor #5	(5.25, 6.45, 7.65)	(6.54, 7.20, 7.86)	(1.68, 2.45, 3.22)	(5.10, 6.10, 7.00)	(3.05, 4.58, 6.10)
Contractor #6	(7.94, 8.20, 8.45)	(2.50, 3.03, 3.56)	(1.62, 2.51, 3.40)	(4.56, 4.90, 5.24)	(6.18, 6.80, 7.42)
Contractor #7	(5.46, 6.14, 6.82)	(3.26, 4.97, 6.67)	(4.55, 5.21, 5.87)	(3.48, 4.88, 6.27)	(6.14, 7.00, 7.86)

suitable linguistic terms. A fuzzy set is characterized by its MF. Similarly, the inference mechanism simulates experts' decisions (DMs) by carrying out reasoning process to achieve the expected outcomes. Then, the defuzzification is performed to obtain non-fuzzy outcomes from the inferred actions by the inference engine. In this study, the fuzzified values ($\tilde{r}_{ij}$) were calculated for each contractor by employing Eq. 8. The outcomes are presented in Table 8. For instance, $\tilde{r}_{11} = (0.58,\ 0.74,\ 0.9)$ is the fuzzified rate for contractor #1 against the criteria #1. $\tilde{r}_{23} = (0.16,\ 0.35,\ 0.53)$ is the fuzzified rating value for contractor #2 against the criteria #3. Similarly, $\tilde{r}_{34} = (0.39,\ 0.57,\ 0.74)$ is the fuzzified rating value allocated for the contractor #3 against the criteria #4 and so on. The calculations for fuzzification process are as follows:

$$\tilde{r}_{11} = \left(\frac{5.21}{9}, \frac{6.68}{9}, \frac{8.14}{9}\right) = (0.58, 0.74, 0.90)$$

$$\tilde{r}_{23} = \left(\frac{1.36}{8.56}, \frac{2.96}{8.56}, \frac{4.56}{8.56}\right) = (0.16, 0.35, 0.53)$$

$$\tilde{r}_{34} = \left(\frac{2.25}{5.71}, \frac{3.25}{5.71}, \frac{4.25}{5.71}\right) = (0.39, 0.57, 0.74).$$

In the end, the data obtained for $\tilde{R}_{ij}$ are a matrix presenting the fuzzy membership degree of contractors for the main criteria. Each data in the matrix shows the performance of contractors allocated by the DMs. For instance, $\tilde{R}_{11}$ shows the fuzzified numerical data of contractor #1 for all the main criteria set and depicts the strength of contractor #1.

Table 8 Fuzzy membership degrees of contractor with regard to the criteria

Contractors	Criteria set				
	u_1	u_2	u_3	u_4	u_5
Contractor #1	(0.58, 0.74, 0.9)	(0.87, 0.93, 1.0)	(0.41, 0.58, 0.76)	(0.61, 0.72, 0.83)	(0.27, 0.49, 0.7)
Contractor #2	(0.55, 0.74, 0.93)	(0.73, 0.86, 1.0)	(0.16, 0.35, 0.53)	(0.40, 0.58, 0.76)	(0.68, 0.81, 0.93)
Contractor #3	(0.6, 0.8, 1.0)	(0.55, 0.74, 0.93)	(0.48, 0.67, 0.85)	(0.39, 0.57, 0.74)	(0.39, 0.56, 0.74)
Contractor #4	(0.87, 0.93, 1.0)	(0.48, 0.61, 0.74)	(0.34, 0.43, 0.53)	(0.68, 0.78, 0.88)	(0.28, 0.33, 0.38)
Contractor #5	(0.67, 0.82, 0.97)	(0.83, 0.92, 1.0)	(0.21, 0.31, 0.41)	(0.65, 0.77, 0.89)	(0.39, 0.58, 0.78)
Contractor #6	(0.94, 0.97, 1.0)	(0.30, 0.36, 0.42)	(0.19, 0.30, 0.40)	(0.54, 0.58, 0.62)	(0.73, 0.80, 0.88)
Contractor #7	(0.69, 0.78, 0.88)	(0.41, 0.63, 0.85)	(0.58, 0.66, 0.75)	(0.44, 0.62, 0.79)	(0.78, 0.89, 1.0)
Weight of criteria (w_{ii})	(0.25, 0.32, 0.39)	(0.45, 0.52, 0.61)	(0.05, 006, 0.09)	(0.05, 0.06, 0.08)	(0.04, 0.05, 0.06)

$$\tilde{R}_{11} = [(0.58,\ 0.74,\ 0.9),\ (0.87,\ 0.93,\ 1.0),\ (0.41,\ 0.58,\ 0.76),\ (0.61,\ 0.72,\ 0.83),\ (0.27,\ 0.49,\ 0.7)].$$

The weighted fuzzy performance rates of contractors with regard to the criteria are determined by employing Eq. 9, and the findings are presented in Table 9. The unification of performance rate data for each contractor with regard to main criteria is difficult enough with traditional methods; however, it is necessary because the data depicting the performance of contractor are Big Data and the processing of these data by traditional methods might not be possible. They need to be processed, compared and merged to make substantial decision for the contractor selection. The reason is that because one contractor is going to be awarded for the construction project, and all others will be rejected. The accept or reject process must be convincing and justified. Therefore, the guides and steps on how to select a contractor for a job and assign weights for each criterion are very important.

The performance rate of some contractors is calculated and presented below. For instance, $V_{11} = (0.15, 0.24, 0.35)$ is a weighted fuzzy triangular rate of contractor #1, which depicts the performance index of contractor #1 for the 'financial situation' of the contractor. $V_{22} = (0.33, 0.45, 0.61)$ is a weighted fuzzy triangular rate of contractor #2 for depicting the 'management capability' of this contractor. Similarly, all V_{ij} is calculated in terms of fuzzy triangular numerical data and presented in Table 9.

$$\tilde{V}_{11} = \tilde{r}_{11}(.)\tilde{w}_1 = (0.58,\ 0.74,\ 0.9)\ (.)\ (0.25,\ 0.32,\ 0.39) = (0.15,\ 0.24,\ 0.35)$$

$$\tilde{V}_{15} = \tilde{r}_{15}(.)\tilde{w}_5 = (0.27,\ 0.49,\ 0.7)\ (.)\ (0.04,\ 0.05,\ 0.06) = (0.01,\ 0.03,\ 0.04)$$

$$\tilde{V}_{22} = \tilde{r}_{22}(.)\tilde{w}_2 = (0.73,\ 0.86,\ 1.0)(.)(0.45,\ 0.52,\ 0.61) = (0.33,\ 0.45,\ 0.61).$$

The data in Table 9 show the performance rate of all contractors assessed against each criterion. The performance indicators are triangular fuzzified rates which are not very meaningful to analyzation. This case study revealed that taking the advantage of Big Data is an evolutionary process in which the understanding of the potential, the assessment and processing of Big Data and the routinization of processes played a crucial role. Hence, the weighted data of fuzzy performance indicators need to be normalized. The normalization of fuzzified data means defuzzification of them which aims to determine the distance of each performance indicator to the ideal value. However, the distances can be on both sides of the ideal values, and then one can define fuzzy positive-ideal solution (FPIS, I*) and fuzzy negative-ideal solution (FNIS, I^-) to determine the position of the contractors. The formulations of this definition are presented below.

$I^* = \left(\tilde{v}_1^*, \tilde{v}_2^*, \ldots, \tilde{v}_n^*\right)$, $I^- = \left(\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-\right)$, where $\tilde{v}_j^* = (1,1,1)$ and $\tilde{v}_j^- = (0,0,0)$, $j = 1,2,\ldots,n$.

Hence,

$$I^* = [(1,\ 1,\ 1),\ (1,\ 1,\ 1),\ (1,\ 1,\ 1),\ (1,\ 1,\ 1),\ (1,\ 1,\ 1)]$$
$$I^- = [(0,\ 0,\ 0),\ (0,\ 0,\ 0),\ (0,\ 0,\ 0),\ (0,\ 0,\ 0),\ (0,\ 0,\ 0)]$$

The distance of performance of each contractor from the fuzzy positive-ideal solution (FPIS), I*; I_i (i = 1,2,…,m), can be calculated by Eq. 10.

$$d_i^+ = \sqrt{\left(\sum_{j=1}^{n}\left(v_{ij} - v_j^+\right)^2\right)} \quad i = 1,\ 2,\ldots,m \tag{10}$$

Similarly, the distance of performance of each alternative contractor from the fuzzy negative-ideal solution (FNIS) I^- can be calculated by Eq. (11).

Table 9 Weighted fuzzy performance rating of contractors

Contractors	Criteria set				
	u_1	u_2	u_3	u_4	u_5
Contractor #1	(0.15, 0.24, 0.35)	(0.39, 0.49, 0.61)	(0.021, 0.035, 0.068)	(0.031, 0.043, 0.07)	(0.011, 0.025, 0.042)
Contractor #2	(0.14, 0.24, 0.36)	(0.33, 0.45, 0.61)	(0.008, 0.021, 0.048)	(0.02, 0.035, 0.061)	(0.027, 0.041, 0.056)
Contractor #3	(0.15, 0.26, 0.39)	(0.25, 0.39, 0.57)	(0.024, 0.04, 0.077)	(0.02, 0.034, 0.059)	(0.016, 0.028, 0.044)
Contractor #4	(0.22, 0.30, 0.39)	(0.22, 0.32, 0.45)	(0.017, 0.026, 0.048)	(0.034, 0.047, 0.07)	(0.011, 0.017, 0.023)
Contractor #5	(0.17, 0.26, 0.38)	(0.36, 0.48, 0.61)	(0.011, 0.019, 0.037)	(0.033, 0.046, 0.07)	(0.016, 0.029, 0.047)
Contractor #6	(0.24, 0.31, 0.39)	(0.14, 0.19, 0.26)	(0.01, 0.018, 0.036)	(0.027, 0.035, 0.05)	(0.029, 0.04, 0.053)
Contractor #7	(0.17, 0.25, 0.34)	(0.19, 0.33, 0.52)	(0.029, 0.04, 0.068)	(0.022, 0.037, 0.063)	(0.031, 0.045, 0.06)

Table 10 Closeness coefficient of contractors for decision making

Contractors	FPIS (d_i^*)	FNIS (d_i^-)	Closeness coefficient (CC_i)	Efficiency rate (%)	Ranking order of contractors
Contractor #1	4.150	0.889	0.175	99.43	2
Contractor #2	4.202	0.855	0.169	96.02	3
Contractor #3	4.236	0.833	0.163	92.61	4
Contractor #4	4.280	0.757	0.150	85.23	6
Contractor #5	4.160	0.887	0.176	100.00	1
Contractor #6	4.400	0.627	0.124	70.45	7
Contractor #7	4.284	0.775	0.153	86.93	5

$$d_i^- = \sqrt{\left(\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2\right)} \quad i = 1, 2, \ldots, m. \tag{11}$$

The closeness of all contractors to the ideal value was calculated and is presented in Table 10. Then, the FPIS (I*) and FNIS (I^-) of contractor companies were used to calculate the total distances from the ideal values and the closeness coefficient (CC). Chen [50] suggested the vertex method to determine the distance between two triangular fuzzy numerical data, for the linear MFs, the distance of performance value for a contractor U_i $(i = 1, 2,\ldots,m)$ from I* and I^- can be calculated as follows, respectively:

$$d_1^+ = \sqrt{\sum_{j=1}^{n}(0.758) + (0.511) + (0.959) + (0.952) + (0.974)}$$
$$= 4.15$$

$$d_1^- = \sqrt{\sum_{j=1}^{n}(0.259) + (0.505) + (0.046) + (0.051) + (0.029)}$$
$$= 0.889$$

Hence, the calculation of distances for each contractor company has been carried out and is presented in Table 10.

The CC of each alternative contractor was determined by Eq. 10 and 11, respectively. $d(d_i^*, d_i^-)$ shows the distance between two fuzzy numerical data. The CC is used to determine the performance rate of the contractor. In this context, the d_i^* and d_i^- of each alternative contractor A_i $(i = 1, 2,\ldots.,m)$ were calculated, and then the decision was made by ordering them. Some sample calculations were presented below. Hence, if a contractor company (A_i) is closer to the ideal positive solution FPIS (A^*), it will be farther from the fuzzy negative solution [FNIS (A^-)] as CC_i approaches to 1. Hence, considering the CC, the performance rate of contractors can be determined and the best contractor can be selected among seven alternatives. The ordering rate of contractors' performance based on CC can be calculated as follows, and the findings are presented in Table 10.

$$\begin{aligned} CC_i &= \frac{d_i^-}{d_i^* + d_i^-} \quad i = 1, 2, \ldots, m \\ CC_1 &= \frac{2.695}{2.491 + 2.695} = 0.520, \\ CC_2 &= \frac{2.621}{2.727 + 2.621} = 0.490, \\ CC_3 &= \frac{2.835}{2.710 + 2.835} = 0.511 \end{aligned} \tag{12}$$

The similarity measure quantified the meaning of nearest contractor, and the calculations showed that the similarity coefficient of contractor #5 is 0.176 which means that this contractor is a closest prototype to the ideal solution. Hence, the efficiency rate of this contractor was considered to be 100%. The similarity coefficient of contractor #1 is 0.175; hence, this contractor is also close to the ideal solution, however, in the second order and the efficiency rate of it is 99.43%. The similarity coefficient of the other contractors was calculated in the same way, and their efficiency rate was determined. Figure 3 shows the efficiency rate of all contractors in the ranking order. The ordering of contractors is as follows:

Fig. 3 Ranking order of contractors

$$\text{Contractor}\ \#5 > \text{Contractor}\ \#1 > \text{Contractor}\ \#2 > \text{Contractor}\ \#3 > \text{Contractor}\ \#7 > \text{Contractor}\ \#4 > \text{Contractor}\ \#6.$$

4 Discussions

This study covers the combination of two different methods for determining the contractors' eligibility using fuzzy and numerical data. These data were used for ranking the order of contractors in terms of their strength and efficiency for carrying certain jobs. Fuzzy AHP was used initially to determine the weights of criteria. Then fuzzy TOPSIS method was employed for contractor selection. As it is known, the criteria for selection are not equally important, and the related data are not known precisely. This is the most difficult and hardest part of the applications of fuzzy sets and systems. The discussions are usually due to the subjectivity of decision criteria which may change from person to person. However, the goal of contractor selection process is the reduction of construction project risk, maximizing the overall value to the project owner, and building long-term relationships between members of the project. The size of available data is very large and beyond the capacity of a human DM to evaluate, process and then make decision.

Due to its nature, contractor evaluation process is considered as a MCDM problem. A wide range of necessary and sufficient parameters are evaluated to assess the contractors' capabilities. Fuzzy set and systems are able to solve the subjectivity of decision criteria. The suggested approach helps to select the best contractor, or share the project between equally strong contractors. This method has a potential application as decision support system (DSS) in the future, instead of the current procedure applied by the Contractor Classification Agency in the Kingdom of Saudi Arabia.

5 Conclusions

The construction sector of Saudi Arabia is growing, and the country is nowadays like a giant construction site. There are many ongoing mega projects, to meet the requirements of these projects successfully, with high management quality and capability, and on-time delivery; the contractors must be carefully selected. The failure in projects due to the unqualified contractor selection might cause wasting billions of dollars which will negatively affect to the economy of country. There are several challenges in decision making for contractor selection; for instance, Big Data posing high danger to organizations due to integration of complex and large datasets. On the other hand, getting started with the construction projects require Big Datas due to the large size of decision criteria, and the lack of availability of qualified personnel or staff with analytical skills makes it difficult to decide using Big Data. As it is well known, the lowest price is not always the best choice for contractor selection. As it appears in the results, if bids come within a close range (The similarity coefficient and the ranking performance of contractors #5 and #1 are very close), one can interview the contractors again to make a correct decision. In such cases, sharing the project between the contractors might be one of the alternative, or interviewing the contractors in details might be an additional choice for decision making. Interviewing contractors can be carried out by asking several questions that were not considered during the survey. A crucial question might be about the proposed project team, including the qualifications of specific individuals enrolled for fulfillment of the project. For the level and type of involvement, one can expect the contractor to employ highly qualified key personnel such as site supervisor, and project superintendent in the construction project; the contractor's approach to control the cost and expenses; the application of value-engineering and quality management techniques for the project success; the contractor's experience in getting the local approvals; and the relations of contractors with local authorities. The contractor's bonding capability, capacity and insurance coverage of machine and men power employed in project might be also searched during the interviews.

Experts in construction industry mostly agreed that financing capability of contractors plays an important role in obtaining huge opportunities in the market of international construction system. Financial capability is an essential criterion in the initiation of projects or negotiation proposal-type projects. As a conclusion, construction industry has high volatilities, because the cost of materials and equipment is changing very often. On the other hand, there is intensive labor escalation in the market of Kingdom, and moreover, there are more complicated risk factors rising from economic instability and cross-cultural differences than ever. The fuzzy AHP and fuzzy TOPSIS applications might be a perfect base for the future applications of decision support systems.

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Dr. Osman Taylan Osman Taylan is a Professor of Industrial Engineering at King Abdulaziz University. He received the M.Sc. degree in Management Engineering from Istanbul Technical University and Ph.D. in Industrial Engineering from Sakarya University in 1994 and 1999, respectively. His current research interest includes fuzzy multi-criteria decision making, fuzzy linguistic modeling, quality assessment systems, relations between conventional statistical approaches and advanced intelligent systems, and Big Data. Dr. Taylan has published numerous articles in area of adaptive neuro-fuzzy systems, multi-criteria decision making using Big Data, quality assessment of products by fuzzy sets and systems, production systems modeling and information technologies in distinguished journals. He has been teaching statistics, industrial quality control, business forecasting, artificial intelligence and fuzzy logic, operations research and advanced optimization techniques.

Dr. Carlos Porcel Carlos Porcel is associate professor of Computer Science in University of Jaen. He received the M.Sc. and Ph.D. degrees in Computer Science from the University of Granada in 1999 and 2006, respectively. His current research interests include group decision making, linguistic modeling, information retrieval, digital libraries, recommender systems and social media. His h-index is 10 with more than 500 citations received in Web of Science, and four of his publications are considered as highly cited papers in Web of Science. Dr. Porcel is an editorial member of the international journal Applied Soft Computing.

Dr. Enrique Herrera-Viedma Enrique Herrera-Viedma is a Professor of Computer Science and the Vice-President for Research and Transfer in University of Granada. He received the M.Sc. and Ph.D. degrees in Computer Science from the University of Granada in 1993 and 1996, respectively. His current research interests include group decision making, consensus models, linguistic modeling, aggregation of information, information retrieval, bibliometric, digital libraries, web quality evaluation, recommender systems and social media. His h-index is 54 with more than 11,500 citations received in Web of Science. He was identified in 2014, 2015, and 2016 as one of the world's most influential researchers by the Shanghai Center and Thomson Reuters in both Computer Science and Engineering. Dr. Herrera-Viedma is an Associate Editor of several journals such as IEEE Transactions on Systems Man and Cybernetics: Systems, Information Sciences, Int. J. of Fuzzy Systems, Applied Soft Computing and Knowledge-Based Systems.