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ORIGINAL RESEARCH

# Automated two-stage continuous decision support model using exploratory factor analysis-MACBETH-SMART: an application of contractor selection in public sector construction

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**Abstract**
Public sector client marks contractor selection decisions on technical and financial bid considerations where efficient use of public resources is never unheeded. A plethora of past studies has developed two-stage models; however, continuous assessment of contractors is disregarded, and the models compromise on the discontinuous progression that partially recognizes the prominence of the technical stage in the selection process. This research aims to develop a novel automated two-stage continuous decision model for contractors' assessment and selection where each contractor would be assessed on corresponding performance assessment grading levels. Exploratory Factor Analysis (EFA) assimilated with MACBETH (Measuring Attractiveness by a Categorical Based Evaluation Technique) employed to assess the model criteria, whereas, criteria assessment stage is developed using a novel hybrid combination of SMART (Simple Multi-Attribute Rating Technique), which in turn entails the EFA-MACBETH-SMART triplet-combination. The model encompasses extensive model criteria; thus, 76 model criteria were investigated and evaluated. Final selection of a contractor is proposed on technical bid/financial bid ratio mechanisms based on performance levels such as $R_{T/F}$: 80/20; 75/25; 70/30; 65/35; and 60/40. A hypothetical case is encompassed to portray the operational mechanism of the automated assessment system. Findings from the model unveil that continuous progression of technical assessment stage in final selection make justice with the highly qualified contractors, and the likelihood of project success increases. The developed model further conclude that technically highest bidders may be awarded the contract if additionally offers a feasible bid. The developed model preserves the concept of efficient use of public resources alongside supporting the technically highest bidders.

**Keywords** Contractors · SMART · MACBETH · Hybrid system · Multi-criteria decision making · Automation

## 1 Introduction

The public sector accounts for symbolic benefaction in the economic and social augmentation around the globe. This advancement in public works is indispensable; thus, government agencies practice their specific public procurement processes to upkeep the domestic industries and projects (Abdelrahman et al. 2008). A public sector is generally considered a larger sector that undertakes mega projects. This sector trails government's acts and legitimate

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boundaries; thus, public tendering is somewhat multifarious. Kog (2014) proclaim that comparing to the private sector; the public sector strives the most owing to several formalities and legitimate boundaries. In general, private sector clients are unenthusiastic and trail their own tendering process; however, in the public sector, owing to public accountability, the project bid price is a foremost apprehension. Accordingly, most often in the public sector around the globe, the award offers on the lowest bid (Awwad and Ammoury 2019; Cheaitou et al. 2019). This lowest bid award is the most prevailing practice in a competitive bidding system and apparently accountable for efficient use of public resources. Nonetheless, it creates imperfect competition in the market (Brunjes 2020). Persisting many loopholes in the lowest bid price tendering, Brook (2017) critiques this method and propose that tendering should never be situated on the lowest price alone. Awwad Ammoury (2019) also claimed that no doubt the method is the most prevailing, but it does not necessarily fallouts in favour of projects. In persistence to this, many developed countries have already progressed to the multi-criteria selection process.

The theory of multi-criteria selection is the most prevalent and has profound roots in several selection problems. Hashemi et al. (2018) advocate that the multi-criteria decision making (MCDM) approach is an appropriate technique expressly for the contractor selection. A primary element of decision-making is the right choice of MCDM. Since the selection of a contractor is not a tranquil task; hence, thoughtful attention is always required (Khoso and Md Yusof 2020). In recent past, researchers has focused over various MCDM techniques in contractor selection and other relevant models such as in case of contractor selection; Analytical Hierarchy Process (AHP) (Abudayyeh et al. 2007; Yang et al. 2012; Marcarelli and Nappi 2019; Zhao et al. 2019; Gurgun and Koc 2020), Data Envelopment Analysis (DEA) (Yang et al. 2016; Zhao et al. 2019), Analytical Network Process (ANP) (Cheng and Li 2004; Ebrahimnejad et al. 2012; Rashvand et al. 2015; Hasnain et al. 2017), fuzzy set theory (Nieto-Morote and Ruz-Vila 2012; Afshar et al. 2017; Rao and Rathish 2018; Tomczak and Jaśkowski, 2018), TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) (Orkun Alptekin et al. 2017), ELECTRE (ELimination Et Choice Translating Reality) (Marzouk, 2010), PROMETHEE (Preference Ranking Organization METHod for Enrichment of Evaluations) (Semaan and Salem 2017), Analytical Neural Network (ANN) (Safa et al. 2015), VIKOR (Opricovic and Tzeng 2004; Ebrahimnejad et al. 2012; San Cristóbal 2012; Hashemi et al. 2018), and grey theory (Zavadskas et al. 2016). A few algorithms were also presented in past models with similar approaches in different applications such as hybrid robust-stochastic approach (Abedinia et al. 2019), robust optimization approach (Saeedi et al. 2019), meta-heuristic algorithm (Ghadimi et al. 2018), neural networks (Gao et al. 2019), fuzzy decision-making approach (Khodaei et al. 2018), and information gap decision theory (Bagal et al. 2018) etc. Several studies have developed decision support models and systems to overcome the problem of capable contractor selection by considering the technical and financial bids. Rashvand et al. (2015) devised a model for selecting the contractors where the model focused a sole parameter of management capabilities. Likewise, Zhao et al. (2019) developed an efficiency-based system to rank and select the contractor, but regrettably, the study deliberated quite a few model criteria for the system on which the selection is rather questionable. Several similar cases were found where studies have focused quite a few model criteria such as (Cheng and Li 2004; Jr. et al. 2005; Darvish et al. 2009; Watt et al. 2010; Lam and Yu 2011; El-abbasy et al. 2013; Jie et al. 2016; Birjandi et al. 2019; Marcarelli and Nappi, 2019).

Padhi (2010) devised a system in a single-stage mode where the final award was subjected to insufficient criteria besides the inclusion of bid price in the same stage. Similarly, a few other single-stage models were proposed by (Anagnostopoulos and Vavatsikos 2006; Vahdani et al. 2013; Wang et al. 2013; Yang et al. 2016; Semaan and Salem 2017) where the bid price is deliberated during the technical assessment which is in contrast to the public sector procurement procedures around the globe. Other decision models were designed without considering the bid price emulating sole quality based selection which is not pertinent in the public sector, for instance, (Bendaña et al. 2008; Nieto-Morote and Ruz-Vila 2012; Taylan et al. 2017; Hashemi et al. 2018; Tomczak and Jaśkowski 2018). Apart from this, Taylan et al. (2017) applied the theory of big data in contractor selection which in turn entails enormous analytical expertise to assess the contractors, and hence, the model transforms into more burdensome and besides encompasses complex calculations. Likewise, Hashemi et al. (2018) came up with a system of a multifaceted model with enormous calculations; also, the introduction of a grey number with fuzzy turned into an extra vague and uncertain environment.

In addition to the above systems and models, various other attempts have been made to devise a two-stage model where the earlier phase assesses the technical performance among the competitors and the later stage accountable for a financial assessment. However, such models are subjected to dissimilar concepts, and researchers are not agreed on a single suitable solution, for instance, San Cristóbal (2012) developed a two-stage system where a technical assessment was carried out initially, and later the final award was based on project completion time and bid price. Likewise, Liu et al. (2017) designed a two-stage system built on partial least square where the final award was based on health, safety, and environment, technology, and bid price basis.

In contrast, Cheaitou et al. (2019) in their two-stage model selected the final contractor based on risk parameters along-side with bid. Marcarelli Nappi (2019) developed another two-stage model constructed on AHP, wherein after the technical qualification assessment, the final award subjects to the least completion time along with the lowest bid. Zhao et al. (2019) applied efficiency method to prequalify the contractors initially, and later those contractors were allowed to offer any financial bid, and final award is subjected to the consent of Decision Makers (DMs) which is centred on the bid price. In above-discussed models, the case of technical assessment is crystal clear as it encompasses computing and assigning the weights (or weightages) to assessment criteria, however, the concept of bid price and final award is dissimilarly dispensed and also in contrast to the standard procedure of public sector (see Sect. 2 for further details).

Several previous attempts have been made in the estate of decision support models, but none of the models administrated a practical solution based on the current complexity of the construction sector, especially, in recent development in the public sector. Most of the models are situated on the weak foundations of model criteria. A considerable number of studies are unaligned with the adopted public sector procedures around the globe. Several models are overburden with multifarious calculations and also involved arduous procedures whose application in existent circumstance is still doubtful. Apart from the aforementioned problems in past studies, a major point for the research interest is still unexplored and overlooked in the two-stage selection model since the inception of multi-criteria selection. During the initial scrutiny of contractors (i.e., called technical assessment stage), clients set the weightage/marks as a threshold value to either qualify or disqualify the contractors where, subsequently, all qualified contractors are considered equal. A contractor with the highest attained marks in the technical stage is not provided with any leverage, and this process terminates, and the final award is again centred on the minimum offered bid. This contemporary process is based on a discontinuous progression that partially recognizes the prominence of the technical phase. All qualified contractors even which is at the threshold would stand in the same queue competing for contract award, and this does injustice with the highest-ranked contractors, which is also highlighted by Rao Rathish (2018). Nevertheless, this part has not been widely addressed, and the decision models are overlapping with a similar concept. Moreover, studies are not focusing on the applications of models for the public sector on the real ground, and rather their focus is on complex and exceedingly hybrid models. Such models can have applications in academia only, however, the industrial applications are overlooked in those models and their adaptability and applicability are debatable. This needs further investigation in terms of precise contractor assessment, especially in the public sector. Furthermore, the continuity of the technical stage up to the final selection stage and the continuous assessment is a novel research gap and desperately entails further investigation.

The literature is flooded with a plethora of studies in assessment and selection of contractor realm; however, none of the studies has until focused on the continuous assessment model that can subsidy the technical capabilities of competitive contractors in the final selection process while considering the standard public tendering procedure. This paper aims to develop a two-stage model wherein during the first stage (technical stage) the contractors' assessment process is carried out via assessing each contractor through extensive model criteria. The EFA is assimilated with MACBETH to overcome the shortcoming of MACBETH and applied to rank the model criteria. MACBETH assists in computing the model criteria weight using M-MACBETH software. Later, the contractors' performance levels were measured with the aid of SMART. This EFA-MACBETH-SMART triplet-combination is unique and has several fundamental advantages and is being applied for the first time. In the second stage, the technically qualified contractors are allowed to quote a bid price wherein the submitted bids are subjected to strict assessment based on public accountability. This would preserve the idea of efficient use of public resources and at the same time avoids the non-feasible bids and supports technically highest bidders. These two stages are interconnected and based on the novel idea of a continuous assessment model. The entire model is based on an automated assessment process developed in MS Excel spreadsheet. The automated system computes the assessment results of contractors and can assign the performance level accordingly. The system identifies the qualified and dis-qualified contractors and later computes the bid price score and Final Sum Score (FSS) according to the computed assessment levels.

## 1.1 Novelty and contribution

This research investigates the novel two-stage continuous decision support model for contractor's selection. A plethora of past models have been developed, but the idea of continuous assessment is still unexplored. The study proposes a novel combination of MACBETH with SMART (Fig. 1) owing to inherent problems in both techniques when applied individually. The novelty and contribution of this study is briefly presented below and discussed in details in Sect. 10.

1. Extensive model criteria are investigated under three novel categories such as Critical Criteria, Value-Added Criteria, and Desirable Criteria.
2. Simple but a novel hybrid system with a triplet combination of Exploratory Factor Analysis-MACBETH-SMART is introduced, which is entirely a unique concept that has fundamental advantages.

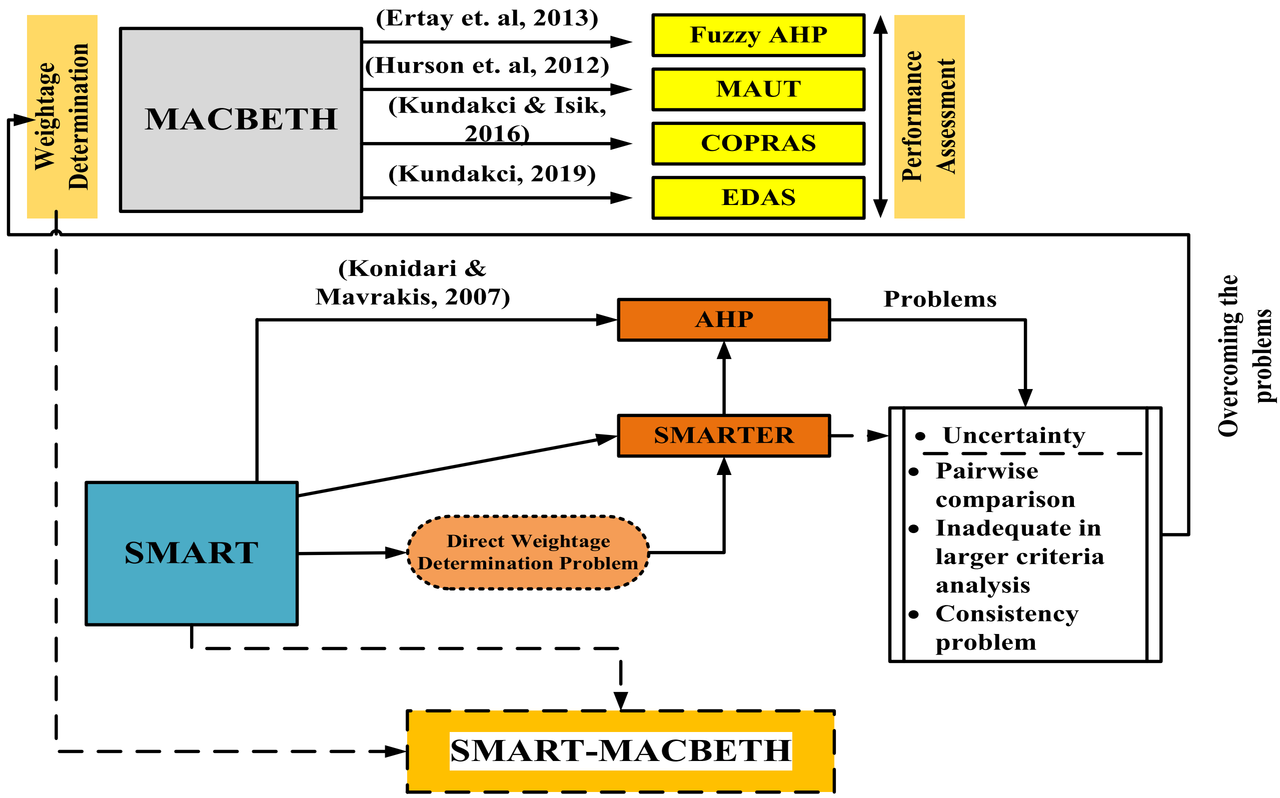



**Fig. 1** A novel MACBETH-SMART integration

3. The proposed model is based on two distinctive but continuous stages which support the continuity of technical stage in the final selection system.
4. Concept of value for money is retained with high priority to the technical stage that serves the major purpose of public sector client.
5. The automated assessment system is an additional contribution for easy and efficient assessment in case of a larger pool of contractors.

The remaining paper is organized as follows. Section 2 highlights the bid evaluation methods developed in the past for financial assessment of contractors. Section 3 presents the insight on MACBETH method and its advantages and shortcomings; similarly, Sect. 4 covers the background of SMART. Research Method is explained in Sect. 5, which also highlights the development of novel MACBETH-SMART model. Section 6 encompasses data collection and preliminary analysis, such as primary tests of EFA. Analysis and Results are covered in three sub-sections under Sect. 7, and model development stages are explained in Sect. 8. A hypothetical case is tested for implementation of the model is presented in Sect. 9, whereas, Sect. 10 highlights the comparison of the proposed model with past related works, and Sect. 11 describes the conclusion of the study.

## 2 Bid evaluation methods

Project cost is curious to clients, especially when dealing with public funds. In addition to this, the existence of a larger number of contractors induces higher competition. Thus, public clients often call for tenders on the lowest bid price amid colossal competition. To break this competition, the lowest responsive bid is typically the possible solution among the public client. However, several other attempts were made in literature in the last few decades to find out a more appropriate way of dealing with price criteria to maintain the quality outcome. In this quest, following several models and indices have been worked out to evaluate the bid price in recent past.

Topcu (2004) developed an extensive model and proposed a system of dealing with the bid price, according to the study, threshold bid values (upper and lower) can be determined using sum and difference of average bid and by considering the standard deviation where all bids beyond those values were discarded. Further, the bid price scores were computed using linear normalization (i.e., lowest bid price/price under consideration), the most commonly employed formula for bid evaluation as claimed by (Ballesteros-Pérez et al. 2013). A few studies proposed that when the selection is based on a bid price basis, a contractor who submits the following bid must be selected i.e. average bid price (Rocha de Gouveia 2002), below the average bid price (Ioannou and Awwad 2010) or using a truncated method (below average bid) after excluding outliers (Waara and Bröchner 2006). In contrast, (Albano et al. 2006) found that the average bid method has numerous drawbacks. Besides, Watt et al. (2010) recommended a straightforward way of dealing with the bid price where any bid 10% below and 10% above the average bid is deemed as minimum acceptable and the best bid respectively. Regrettably, no rationalization is provided for their proposed method.

Teixeira De Almeida (2007) applied the idea of numerical modelling in a bid price solution via a hybrid combination of PROMETHEE and MAUT (Multi-Attribute Utility Theory) along with ELECTRE to compute probability function. The model figured out the best alternative among six different bids by computing the criteria weightages. The proposed model was somewhat equivocal and encompassed an extreme hybrid combination of different techniques that mark this rather problematic to apply in a real scenario. Moreover, appropriate directions to apply the case on different studies were also not addressed. A similar complex model was also developed by Marzouk (2008) based on superiority and inferiority ranking via utilizing SAW (Simple Additive Weighting), TOPSIS, AHP, and MAUT for computing the contractor's final ranking. The cost parameter was handled using the superiority and inferiority model based on SAW and TOPSIS. Later on, another study is presented by Marzouk (2010) but this time author utilized ELECTRE III for contractor selection case. The weightage of the bid was estimated as 25%, and the values to each bid were estimated using credibility score via ELECTRE III. Both studies embroil exhilarating calculation and entail efforts in dealing with the case of bid price criteria. In contrast, Padhi (2010) worked out a system based on the optimization of the bid price, resources, time of project completion, and maintenance period. The system auto-generates the ranking of contractors based on the mentioned criteria. The system, unfortunately, did not devise a separate mechanism of dealing with bid evaluation. The bid price is considered as an inverse function of resources; thus, the system would take the lowest price as an optimized one. A similar approach applied by San Cristóbal (2012) where cost parameters were optimized with other resources using TOPSIS and VIKOR method.

El-Abbasy et al. (2013) developed a simulation-based model wherein the Monte Carlo simulation method was devised to compute optimum index amongst qualification criteria and iteratively bid price weightage. The proposed iterative process was based on a large sum of historical data which may not results in reasonable decisions and can be more problematic to investigate. A similar iterative kind of model was proposed and designed by Safa et al. (2016) using Pareto front optimization where the decision model was trained using several constraints and objectives including; cost, time and other evaluation criteria. However, the model yields a more significant number of solutions, and the final selection was subject to human judgments that could create more shakiness in the justified decision. Awwad Ammoury (2019) employed agent-based modelling to determine the best bid amongst the second-lowest bid, average bid, below average bid, above-average bid, and truncated bid (closet and below the average). The simulation process found that the second-lowest bid price was in favour of the client. In this approach, the concept of the efficient use of public resources was not considered. Similarly, a competitive bidding model is devised by Semaan Salem (2017) founded on optimized bid solutions keeping in view time, cost, safety, and quality as selection criteria. The submitted bids were treated in percentage differences from the maximum submitted bid and minimization of bid and time and maximization of safety and quality were kept under consideration.

Liu et al. (2017) designed a two-stage contractor selection model wherein during the bid evaluation phase, the highest and lowest bids were disregarded in the beginning. Final contractor selection was based on bid price alongside technology and health, safety, and environment parameter correlations. The bid price was treated on a benchmark of standard bid value obtained through a formula, i.e. (considered bid-mean value bid)/mean value bid*100). The highest value goes to any bid closer to this estimate. The problem with approach can be a) no justification of removing the lowest and highest, and b) the mean value itself can be too high or too low and would be on the mercy of other bids. Similarly, Lai et al. (2004) introduced a bid evaluation index that calculates a benchmark value, and any value closer to that benchmark would be provided higher weightage with a maximum of 90 marks. The benchmark value can be calculated as shown in Eq. 1

$$Say,\ valid\ bid = \frac{bid\ price\ submitted\ by\ bidders - baseline\ bid\ given\ by\ owner}{base\ bid} \tag{1}$$

$$Benchmark\ bid = 0.4 * baseline\ bid + 0.6 * average\ of\ valid\ bids$$

The specified approach was quite systematic and beyond the abnormally bid range in terms of baseline bid specified by the owner; however, the problem occurs in the ceiling price. The formula is valid for any value extremely higher than the ceiling price that is not acceptable to public departments. Furthermore, the use of the average bid is again questionable to some extent, as this can increase the project price. Likewise, Ballesteros-Pérez et al. (2015) found that the problem of computing the bid price weightage in the past can handle with the following equations (Eq. 2, 3).

$$bid\ price\ score = \left(1 - \frac{submitted\ bid}{ceiling\ price\ (estimation\ by\ client)}\right) \tag{2}$$

$$bid\ score = \frac{max.\ bid - submitted\ bid}{max.\ bid - min.\ bid} \tag{3}$$

Equation 2 can be used when the ceiling price is known, and the applicability of Eq. 3 is under non-availability of information. However, in both cases, the true representation of the efficient use of public resources is not reflected. It is because a contractor can quote any bid lower than ceiling price in case of Eq. 3, and there are no upper or lower limits in Eq. 2**,** hence, would not be resulted in the feasible solutions.

Looking at the past bid evaluation studies, none of the aforementioned studies has properly resolved the problem of bid evaluation through a rational and simple mechanism. The researches worked out the various disparate solutions of the bid price, which in many cases challenging to compute and implement in the public sector. Moreover, few predictive models required historical data on submitted bids which is challenging to collect, and such models entail the bid data to workout optimum bid with respect to other selection criteria. Such mechanisms are hardly workable in public tendering where qualification assessment takes place at an early stage before bidding. In the aforementioned methods, the weight to bid price and other evaluation criteria are not fully addressed and not covered until now. Moreover, none of the studies has devised a mechanism to benefit the technically high ranked contractors in the final award.

## 3 MACBETH

C.A. Bana e Costa and J.-C. Vansnick developed MACBETH and later modernized and restructured it in 2004. This method is primarily based on linear programming, wherein each element of a set assigned an absolute value say A (Bana 1994). The MACBETH method operates on a qualitative judgment, unlike the classical approaches in AHP and ANP and their families. The final judgment is decided based on the formulation of an additive value model which prioritizes the alternatives with the aid of criteria weights (further details in the form of preliminaries of MACBETH method is described in Appendix A). The method produces impartial and constructive outcomes by considering the fuzziness of the judgment through the seven-point semantic scale of judgment. The semantic scale inherently based on the fuzziness in responses which is a common occurrence in any decision process. Owing to its constructive, and interactive outcome with a property of fuzziness, the qualitative judgments from the path of ordinal data transpired into cardinal preferences.

MACBETH offers several fundamental edges over the classical MCDM methods such as AHP. Its non-numerical pairwise scale converts the method into a simple process (Bana e Costa and Chagas 2004; Cox et al. 2013). The additional perks are catered by its qualitative scale that offers bounteous opportunity to resolve the judgments, and assists in eluding the forceful decisions from DMs (Ertay et al. 2013), and further conveys precise information (Joerin et al. 2010). The method operates on the principle of transpiring the qualitative judgment to quantitative judgment that is rather smooth and easier to understand by DMs while responding judgements. Unlike AHP, the responses are assembled on a qualitative seven-point semantic scale of differences, as shown in Table 1. Moreover, the Saaty scale in AHP does not offer the fuzziness, whereas, this trait is inherently added in the semantic scale that also offers

**Table 1** Semantic scale of differences

| Semantic scale of differences | Quantitative scale | Qualitative equivalent |
|---|---|---|
| Null | 0 | No difference |
| Very weak | 1 | Very weak difference of attractiveness over another |
| Weak | 2 | Weak difference of attractiveness over another |
| Moderate | 3 | Moderate difference of attractiveness over another |
| Strong | 4 | Strong difference of attractiveness over another |
| Very strong | 5 | Very strong difference of attractiveness over another |
| Extremely strong | 6 | Extremely strong difference of attractiveness over another |

additional flexibility in the form of intermediary judgment opportunities to the DMs. Besides the prime perks of scale and flexibility in MACBETH, a major apprehension in the classical MCDM method is the consistency of judgments which is often problematic to the researcher. But thanks to its auto-consistency check and instantaneous validity via a built-in function in M-MACBETH software that eradicates the encumbrance of inconsistency.

The present case of contractor assessment is established on extensive model criteria. The accurate and appropriate assessment of a large number of criteria is often a problem in many MCDM techniques such as in PROMETHEE, AHP, and ANP, etc. The MACBETH has leverage in such circumstances and still delivers fair and precise results irrespective of a larger number of model elements (Madeira et al. 2012). Apart from the several aforementioned dominances of MACBETH, it is also affected by a few shortcomings that are still not unveiled on a larger scale. Unlike AHP and ANP, the weightage computation in MACBETH is a function of criteria order which is on the benevolence of DMs. C. A. Bana et al. (1994) affirm that in MACBETH, the ranking of attributes is conceivable with the support of DMs either in the shape of pairwise judgmental information (swing weights) or via direct consultations with DMs. The swing weight and direct rating approaches in the past have been under tremendous criticism. Owing to several inherent drawbacks, researchers believe that these methods have no scientific approach. While comparing the swing weight method, various studies criticized the method and claimed that this method is rather complex, challenging to apply, less intuitive and has a higher chance of errors (Monat 2009), intricate in the application (Dabrowski 2014; Barfod and Salling 2015), and subjected to variations in outcomes (Winterfeldt and Edwards 1986; Edwards and Barron 1994). In contrast, (Bana e Costa and Chagas 2004; Konidari and Mavrakis 2007) criticized the direct rating method, and asserted that the method is less precise compared to other methods in similar family.

## 4 SMART

SMART is fundamentally derived from MAUT and considered as its simple version (Brugha 2004). The SMART aims to rank the alternatives in a subjective order and offers ratings in performances using an appropriate numerical grading. Besides, SMART computes the performance of any function in the form of distinctive grading levels. It is based on a linear additive model likewise MACBETH, wherein swing weights or direct weighting systems are applied which has fundamental drawbacks as claimed by (Bana et al. 2004). The process of grading assessment in SMART is based on its utility function (Furthermore, the preliminaries of SMART is presented in Appendix B). SMART offers a straightforward process of computing the grades using a simple formula. Although various types of utility functions are available, i.e. linear, non-linear, and exponential, but the linear utility function is recommended in case of independent group judgments (Rayno et al. 1998). There are several shreds of evidence that the linear function is relatively healthy and more comfortable to be interpreted and elicited and also a close approximation (Gómez-Limón and Martínez 2006; André and Riesgo 2007). The linear function has got another advantage of operating without group DMs and also computes similar results as of non-linear and exponential (Konidari and Mavrakis 2007).

Marler Arora (2010) asserted that to know the preferences of DMs, SMART is the most superior technique in decision making and also comfortable in the application. Moreover, they believe that the cognitive complexity level in SMART is much lower even from the simple AHP. Brugha (2004) and Konidari Mavrakis (2007) suggested that SMART is a comprehensive tool for quantitative evaluation and entails less computational efforts comparing to AHP. Chou Chang (2008) linked the popularity of the method with its wide range incorporating quantitative and qualitative criteria. The additional perks of SMART include its powerful assessment method comparing to AHP (Brugha 2004). The additive value model in SMART has numerous advantages such as it represents the true aggregate utility function even in a case if the additive utility independence does not hold precisely (Duarte and Reis 2006). It reduces complexity in the process (Kwak et al. 2001), and provides more robust outcomes during sensitivity analysis as compared to other functions (Kumar and Alappat 2005).

Apart from the several advantages of SMART, the basis of computing weightages in SMART is highly criticized in the recent past. To come up with this problem, Konidari Mavrakis (2007) utilized the AHP-SMART hybrid option where criteria weightage were calculated using AHP, and SMART was employed to assign performance grades. The study found that no doubt the SMART technique is extensive and involves lesser efforts but the process of weightage determination in SMART is not irrational and not acceptable in case of complicated problems. Since the direct weightage method is involved in SMART and depends on the direct judgment of DMs, this creates a problem as their judgments are more subjective (Konidari and Mavrakis 2007). Thus, the weightage assessment process in SMART is shaky and less confident. Owing to discussed fundamental challenges and shortcomings in SMART, the weightage computation process is preferred from MACBETH analysis, whereas, the SMART would compute the performance grading levels. This MACBETH-SMART integration is explained in Sect. 5.

## 5 Research method

Scientific research trails a systematic and structured method to achieve a research goal. The choice of contractor in construction, especially in the public sector is stimulating and arguable that entails a more sophisticated research method. Holt (2010) found that the problem of contractor selection in the public sector is worsening day to day and no distinctive actions have been taken to resolve the problem, rather the studies are getting intricate and no appropriate system developed for the public sector. For a long time, a massive number of studies have emerged in resolving the problems of the private and public sectors; nevertheless, the quest for well-organized and systematic research in the domain of the public sector is still enduring. Also, Khoso Md Yusof (2020) confirmed that the topic of contractor selection had been raised for the last three decades; nonetheless, there are still more avenues of research in this field.

The present investigation focused on extensive model criteria, the building blocks of a model. To come up with more valuable and extensive model criteria, various prominent databases were explored. Published literature followed by interviews with experts laid exhaustive discussion. A novel and an extensive set of criteria were listed out considering the complexity in today's public sector projects. Appropriate classification of model criteria alongside the suitability of criteria as per the public project need was a top priority. With the experts' consultation, 76 model criteria structured into three primary classifications namely; the Critical Criteria (CC), Value-Added Criteria (VAC), and Desirable Criteria (DC) were investigated and evaluated. The data on the level of significance of model criteria were gathered with the aid of a questionnaire. SPSS software tool applied to analyze the significance of model criteria using EFA in the form of Principal Component Analysis (PCA) where the rotation of factors produces the criteria in terms of their significance. At this stage, EFA substitutes the first condition of MACBETH, i.e. ratings of criteria owing to discussed inherent problems in MACBETH (see Sect. 3).

The ranking of model criteria leads to the design of the second questionnaire based on the pairwise semantic scale in MACBETH. Top hierarchy experts from the public sector called for their judgment input on a semantic scale of differences (as per Table 1). The experts' judgments were analyzed in a registered M-MACBETH software (purchased online from http://m-macbeth.com), and model criteria were weighted, modified, and verified through sensitivity analysis. Five different levels of performance grades were designed based on the technical weightage of each contractor. The assessment of each contractor was decided on the utility values computed using the SMART technique, which in turn form a novel combination of MACBETH-SMART. In the recent past, several hybrid combinations of MCDM techniques were employed because the single technique is incapable of resolving the intricate challenges in a few cases. Recently, SMART and MACBETH techniques have been integrated with other methods to get optimum results. For instance, MACBETH-fuzzy AHP (Ertay et al. 2013) in case of renewable energy, MACBETH-MAUT (Hurson et al. 2012) for portfolio selection, MACBETH- COPRAS (Kundakcı and Işık 2016) for air compressor selection, MACBETH-EDAS (Kundakcı 2019) in the application of small and medium-sized enterprises (SME). Further, Konidari Mavrakis (2007) utilized the AHP-SMART combination, but none of the studies has ever employed MACBETH-SMART integration as a hybrid technique (Fig. 1). The MACBETH can serve as an alternative in SMART to evaluate value function. The integration of MACBETH-SMART is simple and straightforward as both techniques have compatibility because of their same origin from MAUT. Moreover, the SMART uses criteria weightage to compute the overall utility value, and MACBETH can efficiently compute the weightage.

In the first stage of the model, each contractor, after qualifying the screening would be technically assessed on most critical model criteria identified from EFA analysis. This stage results in five distinct levels of contractors i.e. not acceptable (L0), hardly acceptable (L1), acceptable (L2), highly acceptable (L3), and outstanding (L4). The second stage of the model scrutinized the submitted bid from (L1–L4) groups of contractors. The bids that are not meeting the purpose of efficient use of public resources (i.e. either too low or higher than government's estimation) would be called non-feasible bids, so, discarded. The final selection of a contractor is a continuous model i.e., technical stage would not be obsolete and the benefits of higher technical weightages would be provided to contractors in the final stage of the financial assessment. This continuous model would assign the weightage to technical and financial bids exclusively based on their respective performance levels. This continuous assessment approach indicates that no two groups (L1–L4) would be treated uniformly, and the higher compensation in bid price is provided to the one who ranked highest in technical assessment tier. This computation is based on an automatic system that initially computes the technical weightages from provided information through strict scrutiny by a team of DMs. Later, based on assigned performance grading levels, the FSS would be calculated that can decide the contract award. This novel

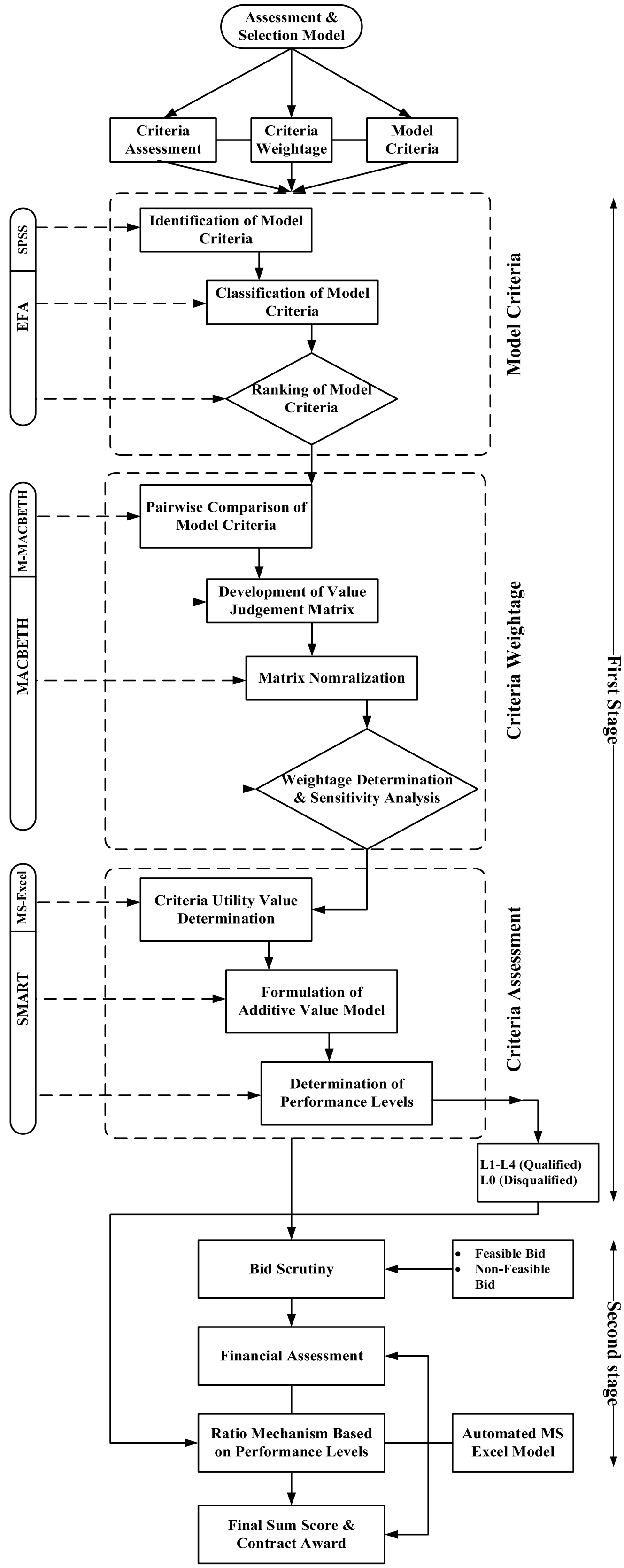



**Fig. 2** Functional research flow based on an employed hybrid system

research design is organized with the aim of achieving fair and rational results. Figure 2 demonstrates the functional research methodology based on hybrid system carried out in this work.

## 6 Data collection and preliminary analysis

Data collection is a fundamental and essential part of scientific research that represents a process of gathering information to answer the research questions, whereas, the data analysis is a process of transforming the data into useful information to support decision making. The most imperative part of this process is to make sure that rich and reliable information was collected. King et al. (1994) asserted that scientific research must follow codified, explicitly, and popular methods to collect and analyze the data. For this present research, two exhaustive questionnaires were designed to collect the data sample. A questionnaire survey is a common and appropriate tool to gather data from the respondents for an empirical study (Wang et al. 2019). A pilot survey was conducted in the form of a pre-expert survey with a few experts. This is conducted to verify the viability of the study before the actual data collection process on large sample size. The pilot survey facilitated in final instrument design and later, experts' survey was conducted to collect the data on a larger sample size. To target the larger sample, an expert sampling technique of purposive sampling method was adopted. This is a non-probabilistic sampling approach that is based on the population characteristics and targets the objectives. This sampling method is generally conducted from renowned personnel of relevant fields. Besides, data sample for this work was collected from highly qualified practitioners from the client, consultants, contractors, and other organizations within Pakistan having rich experience and expertise in public tendering works. The second questionnaire is based on one–one interaction with highly experienced personnel, called here DMs. In total, 15 DMs were targeted to acquire their judgements.

To validate the quality and quantity of data, various screening tests were conducted. In case of EFA analysis, the sample size was confirmed from (Kline 1994; Bryman, A. and Cramer, 1997), according to them, 100 sample size is sufficient for conducting EFA. Whereas, the quality of data was confirmed by measuring the internal consistency of data. The analysis unveils that the Cronbach's alpha value is 0.872, 0.904, and 0.902 for CC, VAC, and DC categories, respectively. The Cronbach's alpha values are greater than the minimum cutoff of 0.7, as suggested by (Phogat and Gupta 2019). Further, the data sample authentication for EFA was examined using two different and the most popular data analysis methods, i.e., Bartlett's Sphericity Test (BST) and Kaiser-Mayer-Olkin (KMO) analysis. BST examines the correlation among the variables using the Chi square test. A significant correlation was found for all three categories of criteria (i.e., $0.000 < 0.05$). Later, the KMO analysis was conducted to confirm the data adequacy for EFA. The KMO value for three criteria categories found as 0.710, 0.809, and 0.809 for CC, VAC, and DC categories, respectively. A value of 0.6 is set as a benchmark for KMO analysis as per the suggestions of (Jeremy et al. 2006).

## 7 Analysis and results

### 7.1 Model criteria

Criteria ranking is a prime step in analyzing the criteria weightage in MACBETH. PCA analysis was computed in SPSS where factor rotation (FR) produces the factor loading (FL) of each sub-criteria. The process of FR does not alter the solutions rather a fair and simple structure of variables emerged as an outcome in the form of FL. The greater the value of FL, the higher the significance of variables and a value of 0.5 is suggested as a cutoff for measuring this significance (Phogat and Gupta 2019). Since several varieties of FR methods are available and its correct choice subjected to the variable correlation; however, for this case, a varimax method is employed which is more systematic and has a tendency to produce fair results (Phogat and Gupta 2019). Each category of criteria was subjected to PCA independently and later rotated to produce the significance variables (model criteria). With this analysis, 73 model criteria (i.e., sub-criteria) were identified as most influential out of 76 whose FL values were greater than the minimum cutoff (i.e., 0.5) see Figs. 3,4,5.

Figure 3 displays the FL results of the CC criteria category, where 32 sub-criteria were analyzed, and 29 were found as the most significant. These sub-criteria were distributed into eight major criteria, as shown in Fig. 3. Similarly, Fig. 4, 5 demonstrate the FL results of VAC and DC categories, respectively. In these categories, none of the sub-criteria was omitted. Besides, the FL, another analysis in the form of Factor Score (FS) was performed to rank the major model criteria. The FS computation is quite simple and therefore attracted many researchers in recent past such as (Madeira et al. 2012; Benson et al. 2016; Jiang and Zhang 2016). Distefano et al. (2009) defined the FS as dividing the highly loaded subsets from the addition of FL in each group. In other words, FS is an average of FL for a particular group. The ranking of criteria and sub-criteria are compiled and demonstrated in descending order, as shown in Fig. 6.

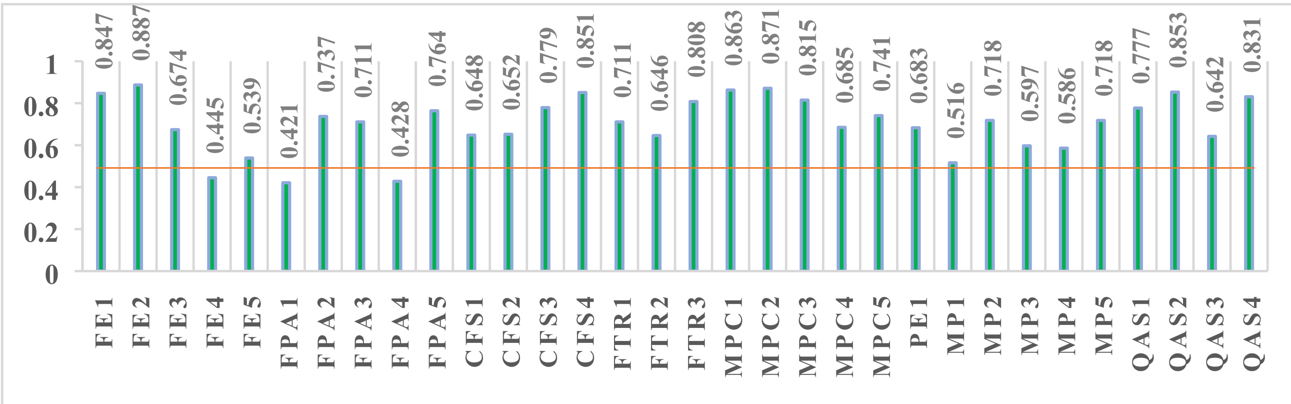



**Fig. 3** Factor loading plotting for sub-criteria of CC category

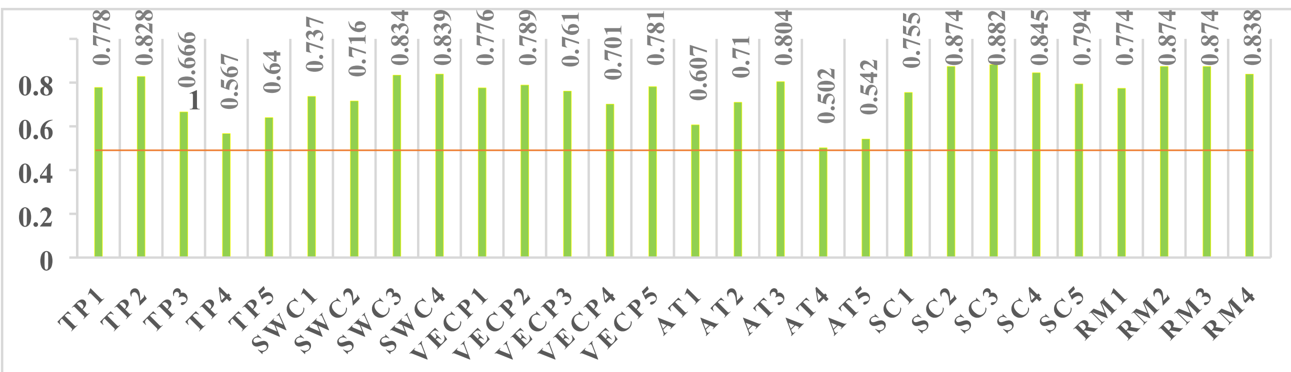



**Fig. 4** Factor loading plotting for sub-criteria of VAC category

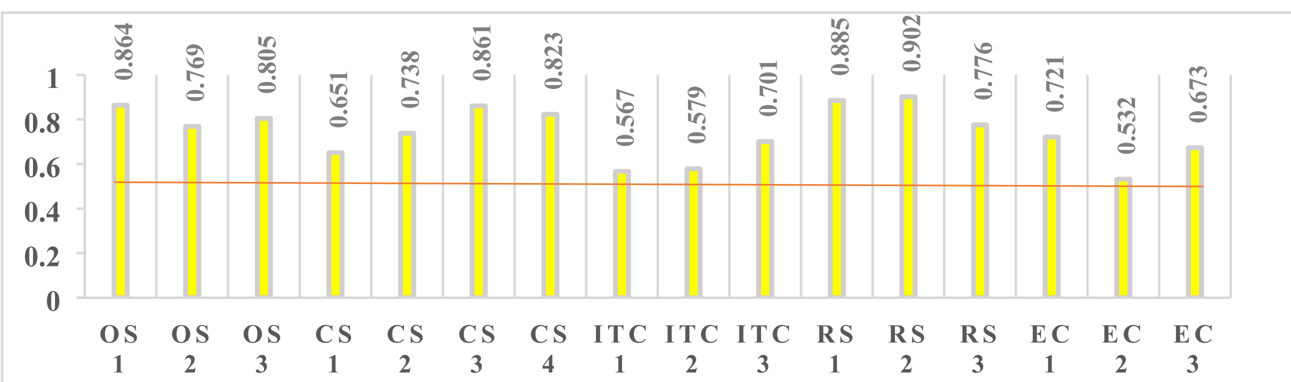



**Fig. 5** Factor loading plotting for sub-criteria of DC category

### 7.2 Criteria weightage

Weightage computation process in MACBETH requires data on a pairwise semantic scale of differences. The essential data from DMs on the second questionnaire was gathered and later analyzed in software, i.e., M-MACBETH. According to C. Bana e Costa et al. (2003), the weightage computation stage converts the ordinal data from 1st Condition into cardinal data using the 2nd Condition of MACBETH's linear programs. The differences of attractiveness on each criterion and sub-criteria were recorded in SPSS and analyzed using median values.

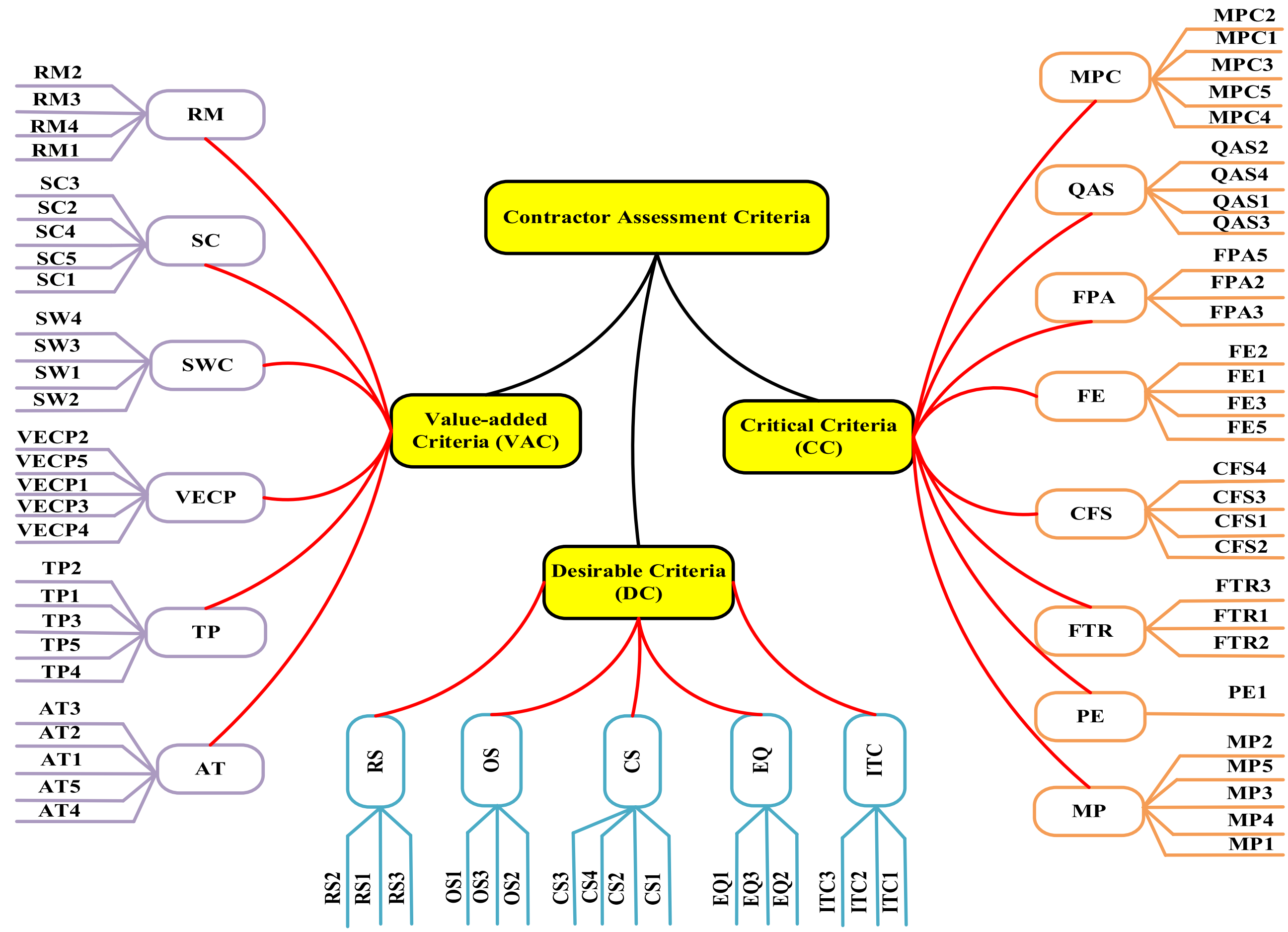



**Fig. 6** Classification and ranking of contractor assessment criteria

The completed judgment matrix was formulated after compiling the results of individual DM, as suggested by (Mateus et al. 2017). MACBETH offers excellent collections of analyzing the criteria weightages among those a top-down hierarchical method was embraced for analysis.

Consistency validity is appalling in MCDM methods; however, with the aid of M-MACBETH, the issue does not persist. Thanks to the software's real-time consistency test and self-adjusting option. When the value-judgment matrix or any of its judgment is inconsistent, the software auto-warns the illogical judgments and the matrix can no longer be analyzed until the consistency problem is resolved. The powerful M-MACBETH auto-suggests different likely patterns to modify the judgments, and after approving, the matrix can be validated and ready for further analysis. Figure 7 illustrates the judgment insertion process and auto-inconsistency judgment detection, and Fig. 8 clears how the inconsistencies are auto-adjusted.

Once the auto-consistency validation is performed, M-MACBETH produces a linear scale showing the criteria weightages on a 0–100 point scale where the top-ranked criteria are assigned a relative weightage of 100, and the remaining criteria are weighted according to the judgments given by DMs. In addition to the scale weight, M-MACBETH also computes a self-normalization matrix where the criteria weightage are auto-normalized, and the normalized weightages can be easily computed. The normalized weightage of criteria is a function of scale weight and can be modified accordingly. Since the scale weight is independent and flexible, therefore, if it requires can be modified by the users. The normalized weightage changes according to the variations performed in the scale weight. This process is carried out whenever the weightage of any specific criteria is either too large so that the weightage of remaining criteria reduces illogically or exceedingly too small to evaluate. This transpires, while making judgments from DMs, henceforth, the true essence of judgments on any criteria does not reflect on such cases. Therefore, scale weights need modifications that otherwise create problems during accurate assessments (Bana E Costa et al. 2008). This inconsistent variation is a result of fluxes in judgments from DMs. In such cases, M-MACBETH offers a

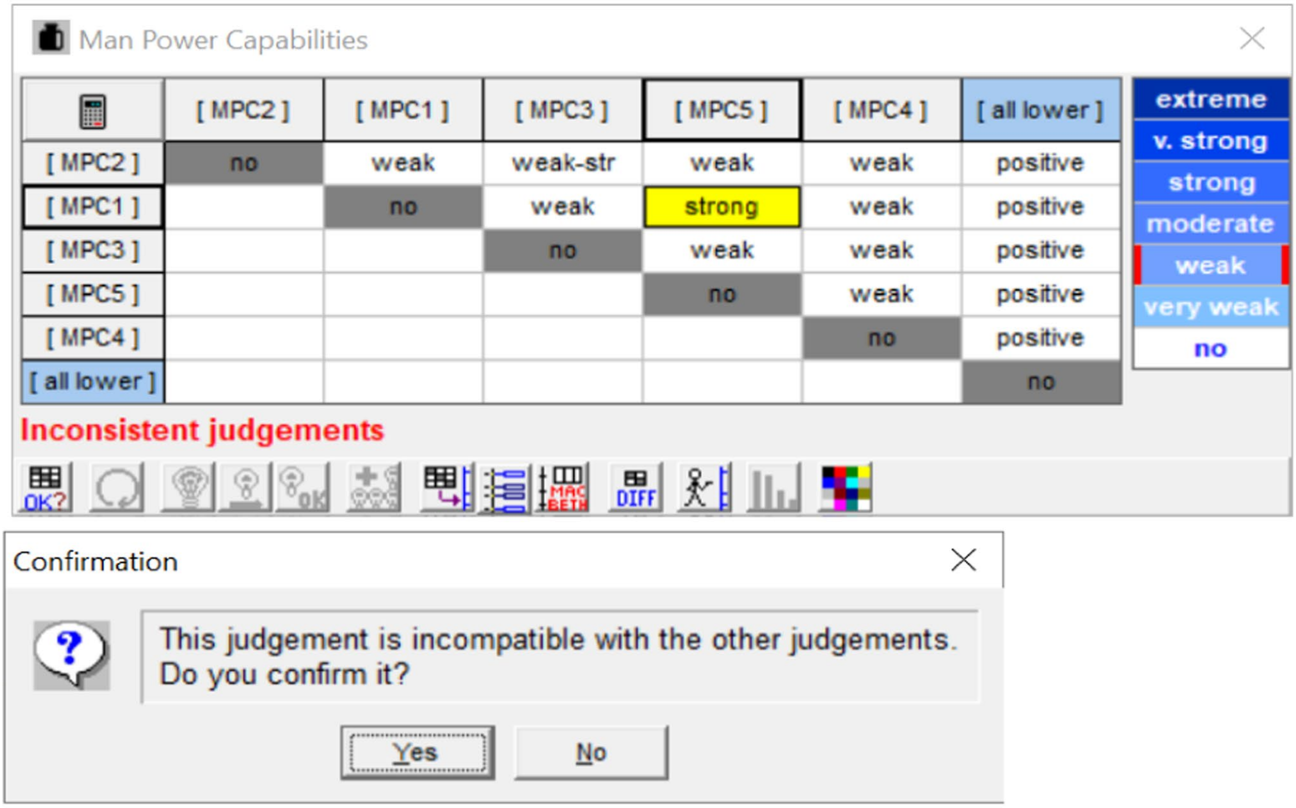



**Fig. 7** Auto detection of inconsistency

powerful and self-adjusting method where users can easily modify the scale weight and at the same time, check the criteria weightage. This process of adjusting and modifying the weightages by observing the effect of one criterion on others is called sensitivity analysis. The advantage of this process is in the form of unfaltering the judgment value matrix.

The process of modifying the scale weight with unfaltering the judgment value matrix is only possible to a certain extent, and the judgment value matrix would be unaltered within the prescribed limits. Thus, M-MACBETH auto offers upper and lower adjusting levels within which the modifications are tolerable, see Figs. 9, 10. The auto-validation approach curtails the human efforts of validating the results from each DM. This process of computing the weightages was applied in the form of top-down hierarchical order, i.e. beginning from the categories of criteria, later the major criteria in each category individually and their sub-criteria. Each time, the judgment value is inserted, auto-checked for consistency, auto-suggested, and validated. This leads to initial scale weight and later, the modified criteria weightage. The computed initial and modified weight of each attribute (categories, major criteria, and sub-criteria) are demonstrated in Table 2.

The attained weightage of major criteria and sub-criteria are later distributed according to their hierarchical distribution such as from categories to major criteria and then to sub-criteria. The distribution of weightage is supported by the aid of the distribution factor (i.e. weightage of parent node). Distribution factors of each parent node weightage were initially calculated and applied to their children nodes. The weightage distribution from parent nodes to children nodes is illustrated in the weightage computation model in Fig. 11a–c.

### 7.3 Criteria assessment

The concept of the criteria assessment was accomplished by employing the SMART technique. The grading assessment was computed using Eq.15 (Appendix B). In the first stage, the grading assessment in the case of each sub-criteria are generated in the form of rubrics, and later, the generated levels are assessed using the basic linear concept of SMART. Distinct grading levels are set for different sub-criterion depending upon their nature. The maximum grading levels are five ranges from 4 to 0 in their decreasing worth. Furthermore, the minimum designed grading are kept up to two levels depending upon the nature of the information

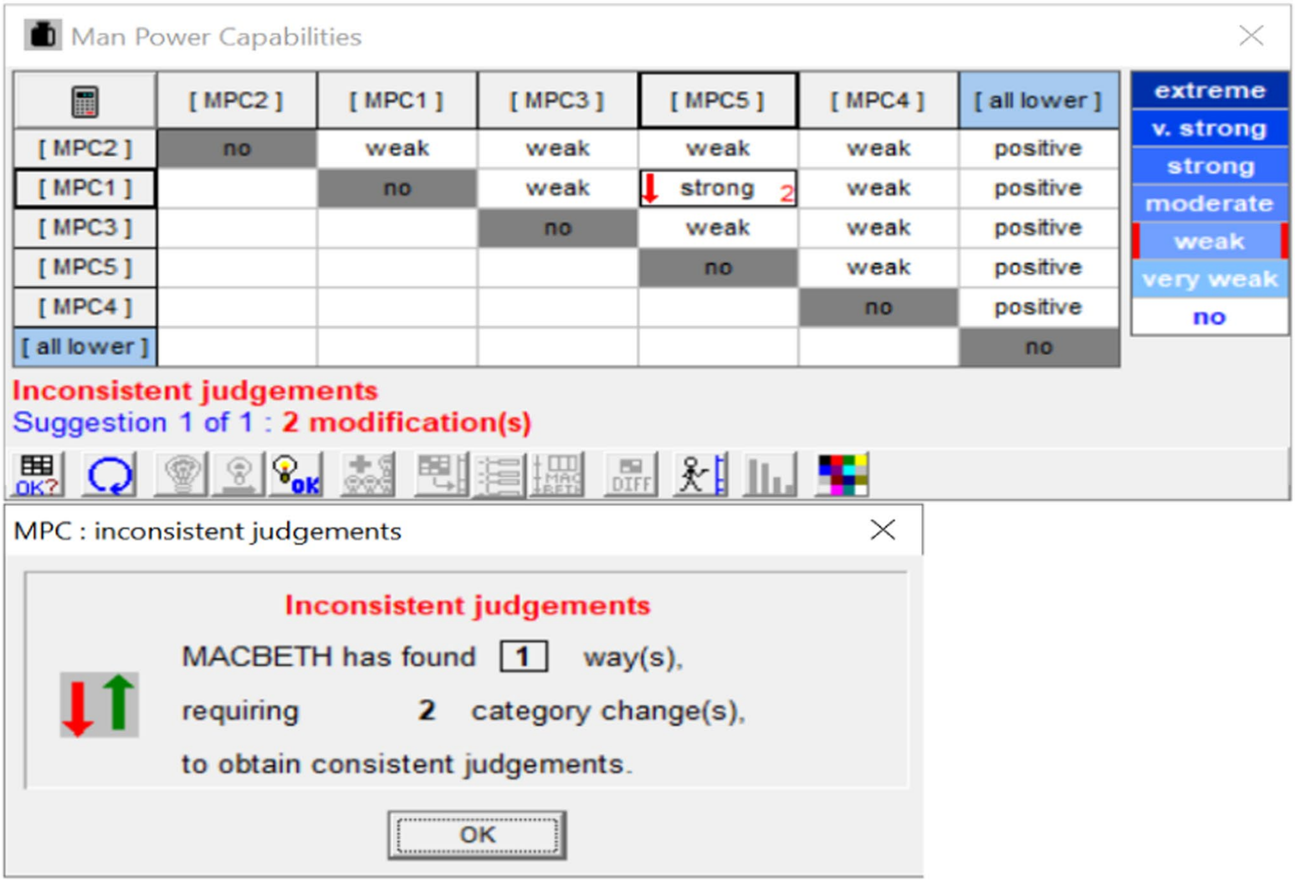



**Fig. 8** Auto-suggestions on modifying the judgement in M-MACBETH inconsistence judgements

contained by the sub-criteria. Table 3 exemplifies the values in case of different grading levels.

In the present model, there are four distinctive grading levels assigned to sub-criteria, i.e., 4–0, 3–0, 2–0, and 1–0 as mentioned in Table 3. The zero is assumed by default minimum value, either the value is assigned or not to any attribute, therefore, $\Delta min$ is the minimum scale value indicating the zero. Furthermore, $\Delta\alpha\beta$, in this case, exemplifies the "considered grading level" that is assigned by the evaluation team to each contractor depending upon their performance levels. Once the grading assessment is devised for each sub-criterion, the next level is to compute their weightages using Eq.15 (Appendix B). The entire process of calculating the weightages is mentioned in the supplementary data file. The purpose of grading assessment weightage is to distribute the parent node weightages to the achieved performance levels. At this stage, SMART is assimilated with the MACBETH technique. Through the SMART assessment levels, each sub-criteria weightage is distributed and the DMs would assign the achieved levels in each sub-criteria, and corresponding weightages would be calculated. Depending upon the total technical bid score ($T_{BS}$), the performance levels of each contractor would be assigned accordingly as described in Table 4.

According to Table 4 five distinctive performance levels can be assigned depending upon the acquired $T_{BS}$ value. For achieving any level (L), a threshold was set, i.e., minimum $T_{BS}$ must be 70 (out of 100). The contractor with the lowest performance level, i.e., the poor performer would be disregarded from further competition. Except for the poor performer, all remaining contractors would be allowed to participate in the final stage of contractor selection, i.e., the financial assessment stage.

## 8 Model development stages

### 8.1 Screening process

An exhaustive screening process is followed to verify the eligibility of competitors before entering the competition. In this regard, elementary information is gathered from each contractor in the form of eligibility criteria. These criteria vary according to government policies and regulations, few

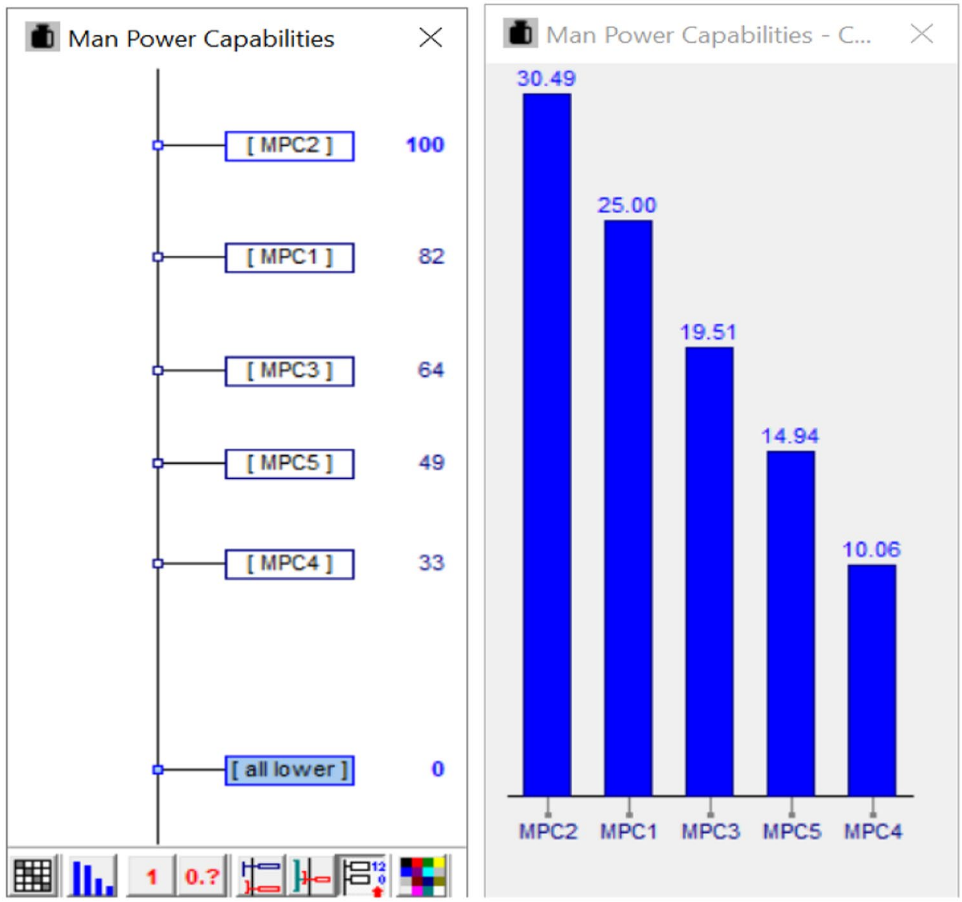



**Fig. 9** Initial scale weight and criteria weight

examples of such criteria are; tax return proofs, a license of work, registration with professional bodies, proof of non-blacklisting, etc. Once the eligibility of the contractor meets, the further process of performance assessment instigates. The successful candidates offered to apply for the technical assessment stage, and those who could not meet any single eligibility criterion would be out of the competition; therefore this is served as knock out stage.

### 8.2 First stage-technical assessment stage

All the eligible contractors can contest for the technical phase of tendering. At this stage, extensive technical criteria are required to meet in order to qualify for the bid stage. These technical criteria are divided into three distinguished categories, i.e., CC, VAC, and DC. Each distinguished set of the category was further classified into major criteria and finally the sub-criteria. The assessment process of each contractor is carried out via the attained grading assessment values, as presented in Table 4.

### 8.3 Second stage-financial assessment stage

Financial assessment in public tendering has a predominant role which is accountable for bid assessment and evaluation. The successful bidders who qualified the technical stage would compete further for the final stage. At this stage, all the contractors from the performance level category of L1–L4 would be entertained, and level L0 would be rejected for further assessment.

In the bid assessment stage, the DMs are responsible for evaluating bid price according to the following classification, i.e., Type A bid -feasible bid; Type B bid-abnormally lowest bid, and Type C bid; above ceiling price bid. Type A bid is subjected to further analysis, and the final decision is centred on the multi-criteria decision, i.e., the combination of technical and financial bid score. Type B bid is consisting of all the marginally low bids, i.e., sufficiently below the engineer's estimation and Type C bid comprises of all overestimation bids as these are not accountable for limited public resources and would be disregarded from the competitive process. The formula for calculating the financial bid score is designed in Eq. 4.

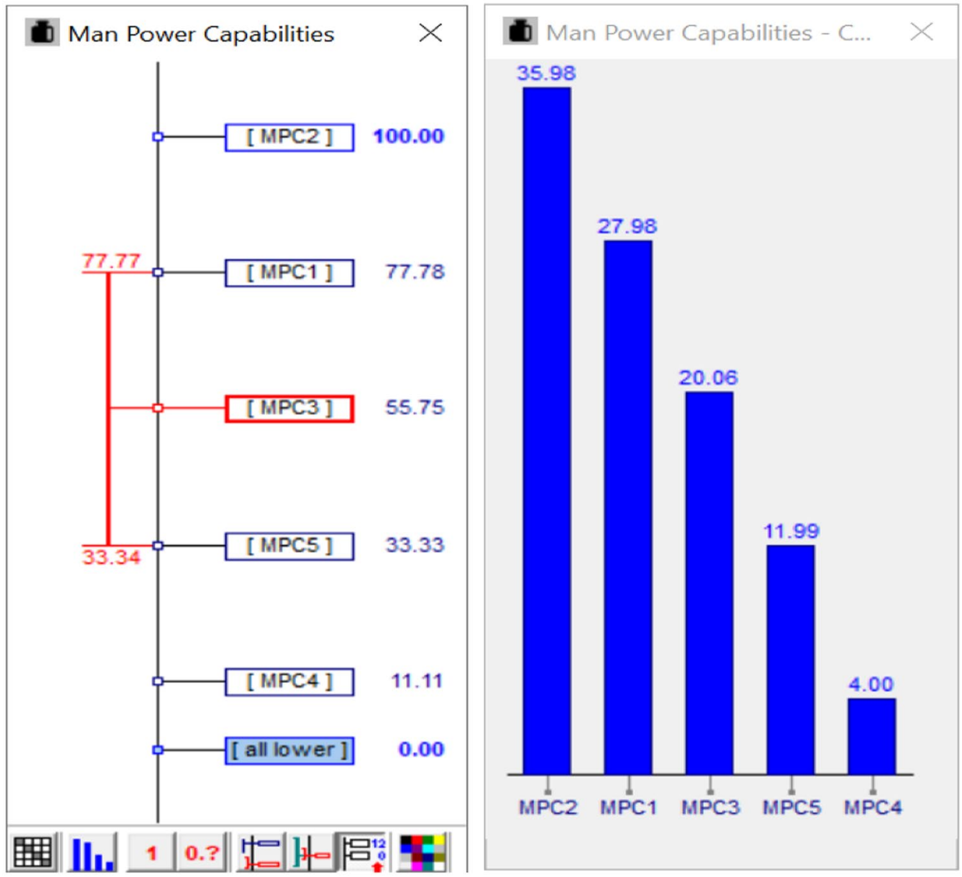



**Fig. 10** Modified scale weight and criteria weight

$$F_{BS} = \frac{Ap * 100}{\mathrm{As}} \tag{4}$$

where;

$Ap$ = Amount of the lowest submitted bid

$As$ = Amount of a bid under consideration

According to Eq. 4, the contractors would get lesser weightage if their bid is above the lowest bid. This would serve two major purposes; firstly, there are no restrictions in quoting any amount of bid as long as the bid is feasible, and secondly, the lowest bid contractor is not always the winner, a common issue in the construction sector for decades.

## 8.4 Final selection Computing-FSS

The final selection of a contractor is based on technical and financial assessment combined weightages. Since during the financial assessment all the contractors who have submitted the overestimated bids are disqualified, so the client is not anxious about the efficient use of public resources as none of the contractors is receiving any benefit of higher profit from public funds. This would augment the satisfaction level of clients as the right value of public funds can be utilized. The final selection of a contractor is proposed distinctly, i.e., there must be continuity of the technical phase in the final selection. Additionally, to anticipate the concept of continuous assessment and providing the benefits of higher technical weightage into bid price in the form of compensation, five distinct continuous ratio mechanisms (technical bid/financial bid, $R_{T/F}$) are suggested as presented in Table 5.

According to the final contractor's selection mechanism mentioned in Table 5, the benefits of technical parameters are reducing with dropping in the performance level. This suggests that higher technical weightages must be assigned to a contractor(s) that has/have higher chances of producing quality performance. Moreover, owing to higher chances of quality performance, the contractor(s) must be given a certain exemption in quoting the least bid price as a discount (but must be feasible bidder). Similarly, the contractor(s) with less performance grading level must quote a bid price closer to the least bid. These contractors would have a likelihood of gaining lesser profits as their bid would have the lesser quoted price comparing to higher performance grading contractors (e.g. L4). The formula of computing the FSS is followed by Eq. 5.

$$\mathrm{FSS} = \mathrm{T_{BS}}^{*}\mathrm{T_{BW}} + \mathrm{F_{BS}}^{*}\mathrm{F_{BW}} \tag{5}$$

where;

FSS = Final sum score

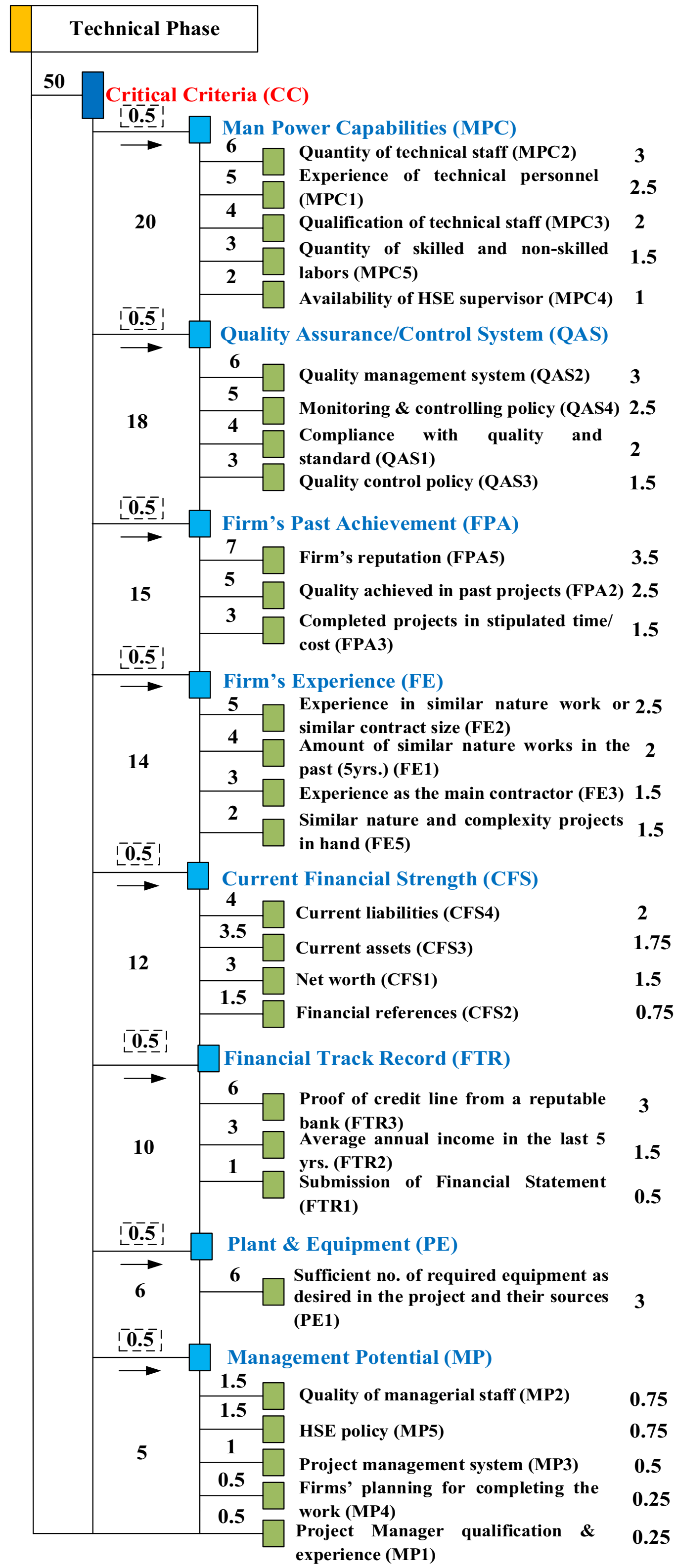
**Table 2** Initial and modified weight of attributes

| Attribute | | Initial Scale Weight | Initial Criteria Weight | Modified Scale Weight | Modified Criteria Weight |
|---|---|---|---|---|---|
| Categories of Criteria | CC | 100 | 58.33 | 100 | 50 |
| | VAC | 57.14 | 33.33 | 60 | 30 |
| | DC | 14.29 | 8.34 | 40 | 20 |
| Major Criteria (CC) | MPC | 100 | 23.36 | 100 | 20 |
| | QAS | 86.83 | 20.33 | 89 | 18 |
| | FPA | 74.43 | 17.29 | 77 | 15 |
| | FE | 60 | 14.02 | 71 | 14 |
| | CFS | 46.67 | 10.98 | 59 | 12 |
| | FTR | 33.33 | 7.71 | 50 | 10 |
| | PE | 20 | 4.67 | 30 | 6 |
| | MP | 6.67 | 1.67 | 24 | 5 |
| Major Criteria (VAC) | RM | 100 | 30.30 | 100 | 25 |
| | SC | 75 | 22.73 | 86 | 22 |
| | SWC | 65 | 19.70 | 79 | 20 |
| | VECP | 55 | 16.67 | 71 | 18 |
| | TP | 30 | 9.09 | 38 | 10 |
| | AT | 5 | 1.52 | 20 | 5 |
| Major Criteria (DC) | RS | 100 | 36.67 | 100 | 30 |
| | OS | 72.73 | 26.67 | 84 | 25 |
| | CS | 54.55 | 20 | 68 | 20 |
| | EQ | 36.36 | 13.33 | 52 | 15 |
| | ITC | 9.09 | 3.33 | 34 | 10 |
| Sub-Criteria (MPC) | MPC2 | 100 | 36 | 100 | 30 |
| | MPC1 | 77.78 | 28 | 82 | 25 |
| | MPC3 | 55.56 | 20 | 64 | 20 |
| | MPC5 | 33.33 | 12 | 49 | 15 |
| | MPC4 | 11.11 | 4 | 33 | 10 |
| Sub-Criteria (QAS) | QAS2 | 100 | 46.16 | 100 | 33 |
| | QAS4 | 66.67 | 30.77 | 80 | 28 |
| | QAS1 | 33.33 | 15.38 | 60 | 22 |
| | QAS3 | 16.67 | 7.69 | 50 | 17 |
| Sub-Criteria (FPA) | FPA5 | 100 | 55.56 | 100 | 47 |
| | FPA2 | 60 | 33.33 | 71 | 33 |
| | FPA3 | 20 | 11.11 | 43 | 20 |
| Sub-Criteria (FE) | FE2 | 100 | 43.75 | 100 | 35 |
| | FE1 | 71.43 | 31.25 | 83 | 29 |
| | FE3 | 42.86 | 18.75 | 63 | 22 |
| | FE5 | 14.29 | 6.25 | 40 | 14 |
| Sub-Criteria (CFS) | CFS4 | 100 | 43.75 | 100 | 34 |
| | CFS3 | 71.43 | 31.25 | 85 | 29 |
| | CFS1 | 42.86 | 18.75 | 73 | 25 |
| | CFS2 | 14.29 | 6.25 | 35 | 12 |
| Sub-Criteria (FTR) | FTR3 | 100 | 55.56 | 100 | 60 |
| | FTR1 | 60 | 33.33 | 50 | 30 |
| | FTR2 | 20 | 11.11 | 17 | 10 |
| Sub-Criteria (PE) | PE1 | 100 | 100 | 100 | 100 |

**Table 2** (continued)

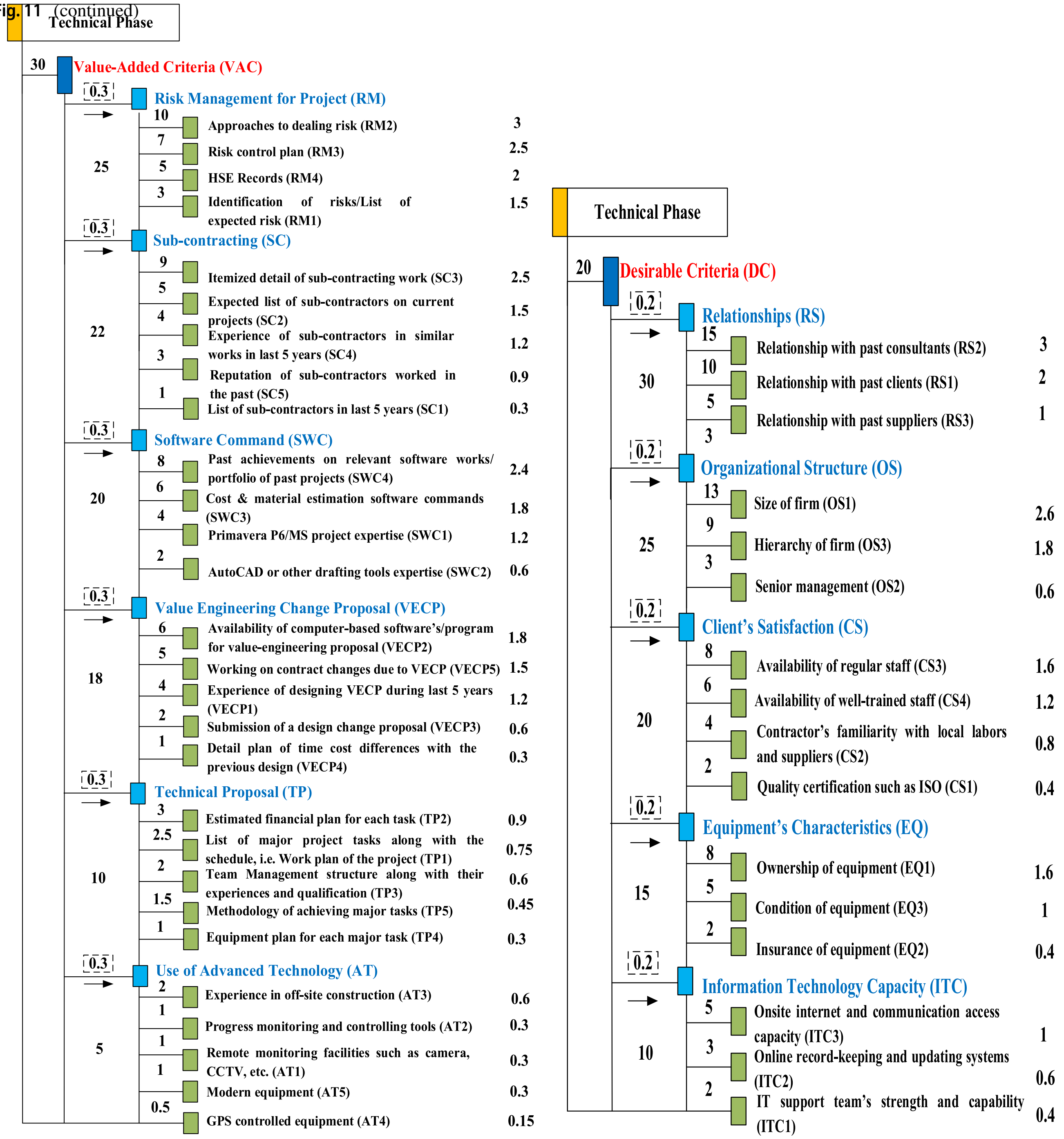
| Attribute | | Initial Scale Weight | Initial Criteria Weight | Modified Scale Weight | Modified Criteria Weight |
|---|---|---|---|---|---|
| Sub-Criteria (MP) | MP2 | 100 | 36 | 100 | 30 |
| | MP5 | 77.78 | 28 | 93 | 28 |
| | MP3 | 55.56 | 20 | 67 | 20 |
| | MP4 | 33.33 | 12 | 40 | 12 |
| | MP1 | 11.11 | 4 | 33 | 10 |
| Sub-Criteria (RM) | RM2 | 100 | 43.75 | 100 | 40 |
| | RM3 | 71.43 | 31.25 | 71 | 28 |
| | RM4 | 42.86 | 18.75 | 50 | 20 |
| | RM1 | 14.29 | 6.25 | 31 | 12 |
| Sub-Criteria (SC) | SC3 | 100 | 46.67 | 100 | 41 |
| | SC2 | 50 | 23.33 | 54 | 22 |
| | SC4 | 35.71 | 16.67 | 45 | 18 |
| | SC5 | 21.43 | 10 | 35 | 14 |
| | SC1 | 7.14 | 3.33 | 11 | 5 |
| Sub-Criteria (SWC) | SWC4 | 100 | 45 | 100 | 40 |
| | SWC3 | 66.67 | 30 | 75 | 30 |
| | SWC1 | 44.44 | 20 | 51 | 20 |
| | SWC2 | 11.11 | 5 | 25 | 10 |
| Sub-Criteria (VECP) | VECP2 | 100 | 36 | 100 | 33 |
| | VECP5 | 77.78 | 28 | 84 | 28 |
| | VECP1 | 55.56 | 20 | 67 | 22 |
| | VECP3 | 33.33 | 12 | 33 | 11 |
| | VECP4 | 11.11 | 4 | 18 | 6 |
| Sub-Criteria (TP) | TP2 | 100 | 36 | 100 | 100 |
| | TP1 | 77.78 | 28 | 84 | 84 |
| | TP3 | 55.56 | 20 | 67 | 67 |
| | TP5 | 33.33 | 12 | 50 | 50 |
| | TP4 | 11.11 | 4 | 34 | 34 |
| Sub-Criteria (AT) | AT3 | 100 | 36.37 | 100 | 40 |
| | AT2 | 75 | 27.27 | 51 | 20 |
| | AT1 | 58.33 | 21.21 | 51 | 20 |
| | AT5 | 33.33 | 12.12 | 25 | 10 |
| | AT4 | 8.33 | 3.03 | 25 | 10 |
| Sub-Criteria (RS) | RS2 | 100 | 55.56 | 100 | 50 |
| | RS1 | 60 | 33.33 | 68 | 34 |
| | RS3 | 20 | 11.11 | 33 | 16 |
| Sub-Criteria (OS) | OS1 | 100 | 55.56 | 100 | 52 |
| | OS3 | 60 | 33.33 | 69 | 36 |
| | OS2 | 20 | 11.11 | 22 | 12 |
| Sub-Criteria (CS) | CS3 | 100 | 43.75 | 100 | 40 |
| | CS4 | 71.43 | 31.25 | 75 | 30 |
| | CS2 | 42.86 | 18.75 | 50 | 20 |
| | CS1 | 14.29 | 6.25 | 25 | 10 |
| Sub-Criteria (EQ) | EQ1 | 100 | 55.56 | 100 | 53 |
| | EQ3 | 60 | 33.33 | 62 | 33 |
| | EQ2 | 20 | 11.11 | 26 | 14 |
| Sub-Criteria (ITC) | ITC3 | 100 | 55.56 | 100 | 50 |
| | ITC2 | 60 | 33.33 | 60 | 30 |
| | ITC1 | 20 | 11.11 | 40 | 20 |

**Fig. 11** **a** Weightage computation model for critical criteria category. **b** Weightage computation model. **c**: Weightage computation model for value-added criteria category for desirable criteria category




**(a)**

Fig. 11 (continued)




(b) (c)

$T_{BS}$ = Technical bid score
$F_{BS}$ = Financial bid score
$T_{BW}$ = Technical bid weightage
$F_{BW}$ = Financial bid weightage

Following the aforementioned stages, a two-stage continuous model is developed, as shown in Fig. 12, having a screening stage alongside two major steps. The initial stage of screening is responsible for the verification of eligibility of contractors. The first major stage is consisting of technical assessment, and in the second stage, the qualified contractors are treated according to their performance grading levels in decreasing order of priority. The financial bids of all qualified contractors are scrutinized where only a feasible bid contractor is further entertained. The final selection

**Table 3** Grading assessment values in different cases using SMART

| Type of cases | Considered grading level | Grading assessment values $V_k = \frac{\Delta\alpha\beta - \Delta min}{\Delta max - \Delta min}$ |
|---|---|---|
| 5 grading levels (max value = 4) | 4 | (4–0)/(4–0) = 1 |
| | 3 | (3–0)/(4–0) = 0.75 |
| | 2 | (2–0)/(4–0) = 0.5 |
| | 1 | (1–0)/(4–0) = 0.25 |
| | 0 | (0–0)/(4–0) = 0 |
| 4 grading levels (max value = 3) | 3 | (3–0)/(3–0) = 1 |
| | 2 | (2–0)/(3–0) = 0.67 |
| | 1 | (1–0)/(3–0) = 0.33 |
| | 0 | (0–0)/(3–0) = 0 |
| 3 grading levels (max value = 2) | 2 | (2–0)/(2–0) = 1 |
| | 1 | (1–0)/(2–0) = 0.5 |
| | 0 | (0–0)/(2–0) = 0 |
| 2 grading levels (max value = 1) | 1 | (1–0)/(1–0) = 1 |
| | 0 | (0–0)/(1–0) = 0 |

**Table 4** Performance levels measurement criteria

| Level | Technical bid Score ($T_{BS}$) | Performance grading Assessment levels (PGAL) |
|---|---|---|
| L4 | $T_{BS}$ = 96–100 | Outstanding |
| L3 | $T_{BS}$ = 90–95 | Very good |
| L2 | $T_{BS}$ = 81–90 | Good |
| L1 | $T_{BS}$ = 70–80 | Hardly accepted |
| L0 | $T_{BS} > 70$ | Poor performer |

stage comprises computing the FSS score that is a combined weightage of technical and financial bid score based on certain percentages associated with each level of contractor's performance. The contractor with the highest FSS score would win the competition.

## 9 Automated two- stages continuous model assessment system- a hypothetical case for implementation

Recent developments in the construction sector along the globe have transpired this industry into a vibrant and multifaceted industry (Abdelmegid et al. 2020). Owing to rapid industrialization, the construction sector entails intricate chores, enormous technological diversity, and multi-operation. However, the public sector in many developed and developing country, especially the task of contractor selection is still at the embryonic stage and still not being ultimately benefited from the automated computerized systems. This automated two-stage continuous model is designed with the aim of considering the simplicity and efficient use. With this aim, a system is developed in MS-Excel ("if" and "AND" statements) that can automatically calculate the technical weightages of each contractor and their corresponding grading levels. It can efficiently deal with the larger pool of contractors and decides their performance levels and ranking.

DMs requires to extract the information from each contractor, and after verifying the eligibility, the system starts operations. The qualitative data from each contractor is firstly converted into quantitative and later inserted (see supplementary data). The system calculates the total technical bid score in the first phase, and the performance grading level would be assigned accordingly. Besides, the auto system can filter the passing and failure contractors based on attained technical weightage and by comparing with threshold values. In the second stage, only passing contractors are called for their bid proposals. The system can calculate the financials bid score, and according to their assigned PGAL level, the FSS can be computed. The operational flow of the entire system is illustrated in Fig. 13.

In order to understand the applicability of the model, a hypothetical example of four contractors is tested. Furthermore, for exemplifying the calculation process of technical assessment, a single contractor is evaluated presently. Nonetheless, with a similar process, as many as contractors can be evaluated quickly without limitation. In the beginning, contractors are already verified for their eligibility and therefore

**Table 5** Contractor's final selection score mechanisms

| Performance Levels of contractors | $R_{T/F}$ (80/20) | | $R_{T/F}$ (75/25) | | $R_{T/F}$ (70/30) | | $R_{T/F}$ (65/35) | | $R_{T/F}$ (60/40) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $T_{BW}$ (%) | $F_{BW}$ (%) | $T_{BW}$ (%) | $F_{BW}$ (%) | $T_{BW}$ (%) | $F_{BW}$ (%) | $T_{BW}$ (%) | $F_{BW}$ (%) | $T_{BW}$ (%) | $F_{BW}$ (%) |
| L4 | 95 | 5 | 90 | 10 | 85 | 15 | 80 | 20 | 75 | 25 |
| L3 | 90 | 10 | 85 | 15 | 80 | 20 | 75 | 25 | 70 | 30 |
| L2 | 85 | 15 | 80 | 20 | 75 | 25 | 70 | 30 | 65 | 35 |
| L1 | 80 | 20 | 75 | 25 | 70 | 30 | 65 | 35 | 60 | 40 |

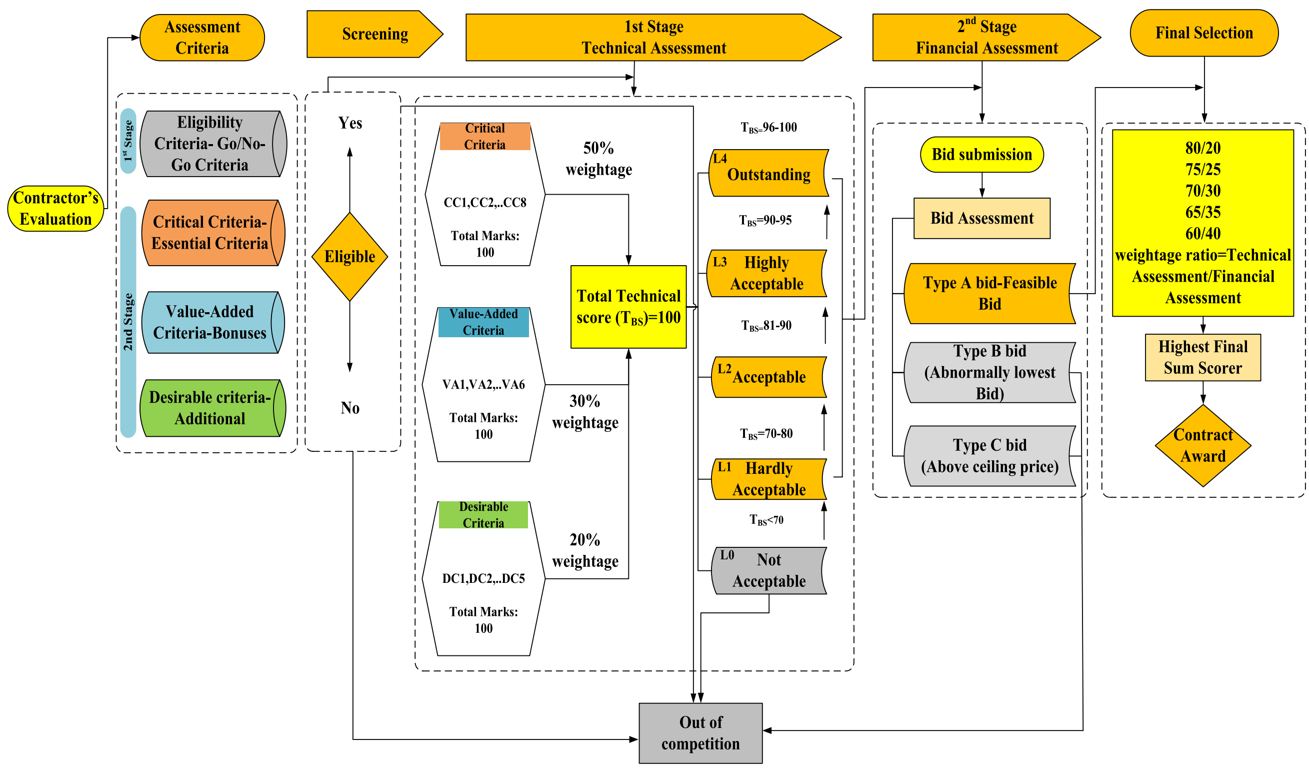



**Fig. 12** A two-stage continuous decision support model for contractors' assessment and selection based on performance grading levels

promoted for the technical assessment. Each contractor was evaluated on 73 sub-criteria divided into three major classifications, as illustrated in Fig. 6. Information on each assessment criterion was inserted in the system where based on the performance criteria, the assigned level was decided. Let us assume, the hypothetical contractor has "N–3" or below the number of technical staff available ("N" will be defined by the client as per project need). In this hypothetical case, the assigned level will be "1" and the corresponding distribution factor will be applied automatically, i.e. 0.75. Similarly, the contractor would be assessed on each technical criteria, and the assigned level would be inserted, and an automatic distribution factor would be assigned. Following this obtained technical score of the contractor would be added, and the corresponding performance level will be assigned (for details see supplementary data file).

The next stage determines the financial bid score. For this hypothetical case, let us assume "σ" represents the minimum proposed bid in (million USD) by any contractor. Furthermore, let the remaining contractors proposed their bid by a certain percentage increment say "σ + 5–20%" for instance; ∅ = variations from 5 to 10% (5%, 7.5%, 10% respectively by each contractors), ∇ = variations from 5 to 15% (5%, 10%, 15% respectively by each contractors, and ϑ = variations from 5 to 20% (5%, 10%, 20% respectively by each contractors). To clarify this further, see Table 6, where 90 possible cases are evaluated to come up with possible solutions. The technical and financial assessments are performed based on an automatic two-stage continuous model assessment system. Table 6 demonstrates the process of possible cases assessed for the award of a project. Each contractor is assessed based on five distinct technical bid/financial bid ratios. The hypothetical case assumes that contractors that fall in the L4 category can never be a minimum bidder and the highest bidder among all. The assumption is only made to simplify the process as if the L4 contractor offers the minimum bid; then this would be a direct winner in any $R_{T/F}$. The following findings are obtained from hypothetical cases.

In the 80/20 ratio, the L4 contractor is the winner in all cases. In the 75/25 ratio, the L3 contractor is a winner only if the L4 contractor quotes a bid of at least 20% above from the minimum bid and at the same time must be a minimum bidder. While applying 70/30 ratio; L3 contractor can win the competition even not being the lowest bidder only if, L4 contractor quotes 20% above from the minimum bid, and L3 should be the second-lowest. Also, L3 contractor can win the contract, if L4 quotes at least 15% above the minimum bid when at the same time L3 should be the minimum bidder. If the client applies 65/35 ratio then; L3 contractor only wins if L4 contractor quotes at least 20% above from the minimum bid when the L1 contractor must be the lowest and if L4 contractor quotes at least 15% above from the minimum

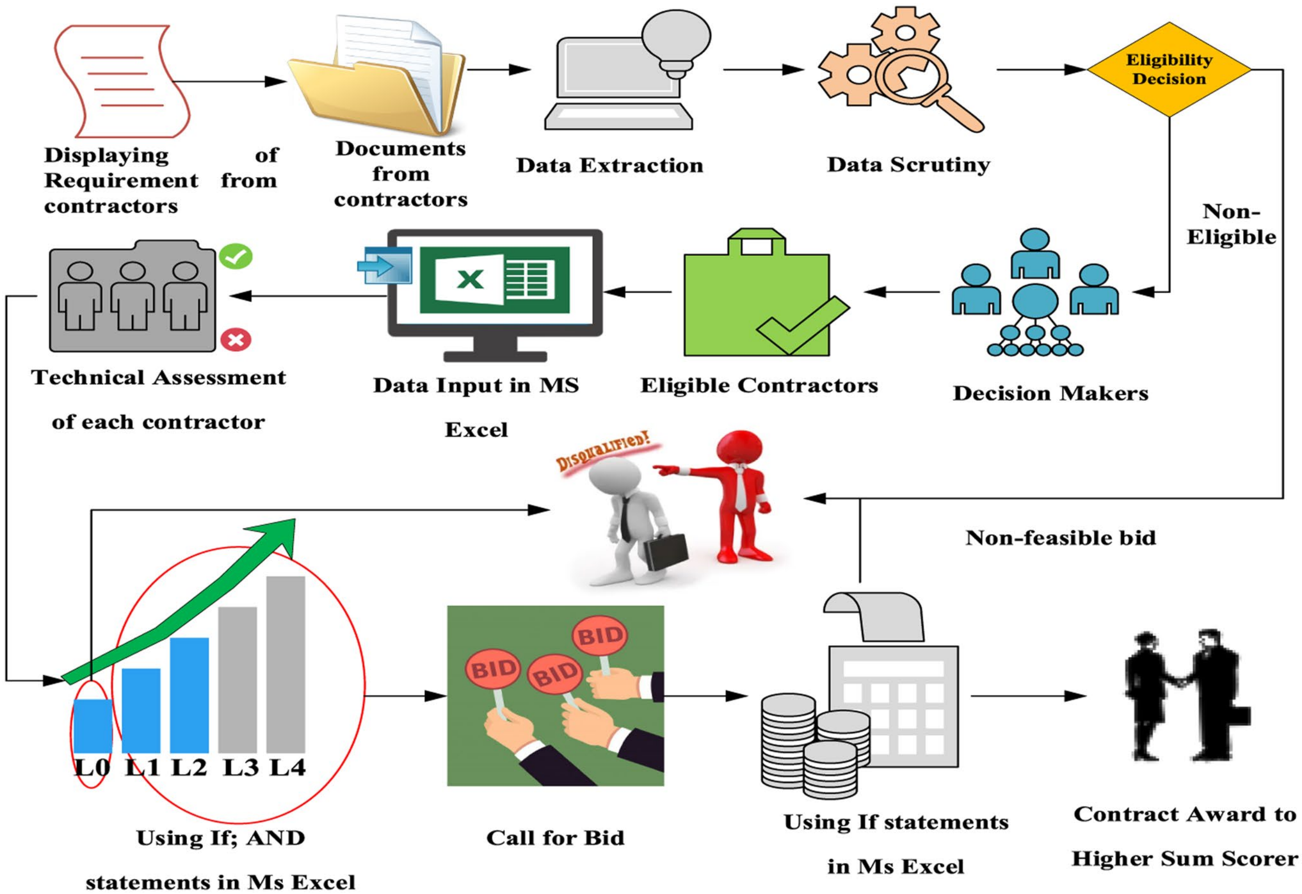



**Fig. 13** Automated two- stages continuous model assessment system operational flow

bid when L3 contractor is the lowest. In last, if 60/40 ratio is chosen; L3 contractor only wins if L4 contractor quotes at least 15% above from the minimum bid when L3 contractor is at 2nd lowest and the L1 contractor is a minimum bidder and if L4 contractor quotes at least 20% above from the minimum bid when L3 contractor is at second-lowest. In case if L3 contractor is the lowest bidder, it must win the competition.

The above findings from hypothetical cases exemplify that the developed system supports a technically highest bidder in the majority of cases. However, other than L4 contractors can also win the project if those contractors compensate in the financial bids and offer higher benefits to the client. Various $R_{T/F}$ are suggested, and those offer almost similar results and support the technical side of the competition when the amount of submitted bid is within the estimation price of the client. However, the client may choose an appropriate $R_{T/F}$ based on the project requisite.

## 10 Model's comparative assessment

The comparison of the developed model with the past models propagates impressive comparative outcomes in five primary directions (Fig. 14).

The critical understanding from the analytical ability drives to compare the appropriate directives for the developed model. The reviewed past models have various shortcomings in the light of the primary element of a contractor selection model, i.e. model criteria. The critical understanding of this essential element found that the model criteria except for some cases lack in various directions. Since the model criteria are key pillars for a robust model, henceforth, their appropriateness can never be ignored. The contemporary models possess a few limitations such as 'limited model criteria' observed in the models of (Cheng and Li 2004; Jr. et al. 2005; Darvish et al. 2009; Watt et al. 2010; Lam and Yu 2011; El-abbasy et al. 2013; Jie et al. 2016; Birjandi et al. 2019; Marcarelli and Nappi, 2019). Similarly, several ambiguous criteria were considered in the studies of (Ebrahimi et al. 2016; Jie et al. 2016; Semaan and Salem, 2017; Birjandi et al. 2019; Cheaitou et al. 2019; Zhao et al. 2019).

**Table 6** Hypothetical case testing for possible rankings of contractors

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 80/20 ratio | | Case 1 (minimum bidder is L1) | | | | | | |
| | | A (L2 is the 2nd lowest bidder) | | | B (L3 is 2nd lowest bidder) | | | |
| | | ∅ | ∇ | ϑ | ∅ | ∇ | ϑ | |
| Ranking | 1st | L4 | L4 | L4 | L4 | L4 | L4 | |
| | 2nd | L3 | L3 | L3 | L3 | L3 | L3 | |
| | 3rd | L2 | L2 | L2 | L2 | L2 | L2 | |
| | 4th | L1 | L1 | L1 | L1 | L1 | L1 | |
| | | Case 2 (minimum bidder is L2) | | | | | | |
| | | A (L1 is the 2nd lowest bidder) | | | B (L3 is the 2nd lowest bidder) | | | |
| | | ∅ | ∇ | ϑ | ∅ | ∇ | ϑ | |
| Ranking | 1st | L4 | L4 | L4 | L4 | L4 | L4 | |
| | 2nd | L3 | L3 | L3 | L3 | L3 | L3 | |
| | 3rd | L2 | L2 | L2 | L2 | L2 | L2 | |
| | 4th | L1 | L1 | L1 | L1 | L1 | L1 | |
| | | Case 3 (minimum bidder is L3) | | | | | | |
| | | A (L1 is the 2nd lowest bidder) | | | B (L2 is the 2nd lowest bidder) | | | |
| | | ∅ | ∇ | ϑ | ∅ | ∇ | ϑ | |
| Ranking | 1st | L4 | L4 | L4 | L4 | L4 | L4 | |
| | 2nd | L3 | L3 | L3 | L3 | L3 | L3 | |
| | 3rd | L2 | L2 | L2 | L2 | L2 | L2 | |
| | 4th | L1 | L1 | L1 | L1 | L1 | L1 | |
| 75/25 ratio | | Case 1 (minimum bidder is L1) | | | | | | |
| | | A (L2 is the 2nd lowest bidder) | | | B (L3 is the 2nd lowest bidder) | | | |
| | | ∅ | ∇ | ϑ | ∅ | ∇ | ϑ | |
| Ranking | 1st | L4 | L4 | L4 | L4 | L4 | L4 | |
| | 2nd | L3 | L3 | L3 | L3 | L3 | L3 | |
| | 3rd | L2 | L2 | L2 | L2 | L2 | L2 | |
| | 4th | L1 | L1 | L1 | L1 | L1 | L1 | |
| | | Case 2 (minimum bidder is L2) | | | | | | |
| | | A (L1 is the 2nd lowest bidder) | | | B (L3 is the 2nd lowest bidder) | | | |
| | | ∅ | ∇ | ϑ | ∅ | ∇ | ϑ | |
| Ranking | 1st | L4 | L4 | L4 | L4 | L4 | L4 | |
| | 2nd | L3 | L3 | L3 | L3 | L3 | L3 | |
| | 3rd | L2 | L2 | L2 | L2 | L2 | L2 | |
| | 4th | L1 | L1 | L1 | L1 | L1 | L1 | |
| | | Case 3 (minimum bidder is L3) | | | | | | |
| | | A (L1 is the 2nd lowest bidder) | | | B (L2 is the 2nd lowest bidder) | | | |
| | | ∅ | ∇ | ϑ | ∅ | ∇ | ϑ | |
| Ranking | 1st | L4 | L4 | L3 | L4 | L4 | L3 | |
| | 2nd | L3 | L3 | L4 | L3 | L3 | L4 | |
| | 3rd | L2 | L2 | L2 | L2 | L2 | L2 | |
| | 4th | L1 | L1 | L1 | L1 | L1 | L1 | |
| 70/30 ratio | | Case 1 (minimum bidder is L1) | | | | | | |
| | | A (L2 is the 2nd lowest bidder) | | | B (L3 is the 2nd lowest bidder) | | | |
| | | ∅ | ∇ | ϑ | ∅ | ∇ | ϑ | |
| Ranking | 1st | L4 | L4 | L4 | L4 | L4 | L3 | |
| | 2nd | L3 | L3 | L3 | L3 | L3 | L4 | |
| | 3rd | L2 | L2 | L2 | L2 | L2 | L2 | |
| | 4th | L1 | L1 | L1 | L1 | L1 | L1 | |

**Table 6** (continued)

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Case 2 (minimum bidder is L2) | | | | | |
| | | A (L1 is the 2nd lowest bidder) | | | B (L3 is the 2nd lowest bidder) | | |
| | | ∅ | ∇ | ϑ | ∅ | ∇ | ϑ |
| Ranking | 1st | L4 | L4 | L4 | L4 | L4 | L3 |
| | 2nd | L3 | L3 | L3 | L3 | L3 | L4 |
| | 3rd | L2 | L2 | L2 | L2 | L2 | L2 |
| | 4th | L1 | L1 | L1 | L1 | L1 | L1 |
| | | Case 3 (minimum bidder is L3) | | | | | |
| | | A (L1 is the 2nd lowest bidder) | | | B (L2 is the 2nd lowest bidder) | | |
| | | ∅ | ∇ | ϑ | ∅ | ∇ | ϑ |
| Ranking | 1st | L4 | L4 | L3 | L4 | L3 | L3 |
| | 2nd | L3 | L3 | L4 | L3 | L4 | L4 |
| | 3rd | L2 | L2 | L2 | L2 | L2 | L2 |
| | 4th | L1 | L1 | L1 | L1 | L1 | L1 |
| 65/35 ratio | | Case 1 (minimum bidder is L1) | | | | | |
| | | A (L2 is the 2nd lowest bidder) | | | B (L3 is the 2nd lowest bidder) | | |
| | | ∅ | ∇ | ϑ | ∅ | ∇ | ϑ |
| Ranking | 1st | L4 | L4 | L4 | L4 | L4 | L3 |
| | 2nd | L3 | L3 | L3 | L3 | L3 | L4 |
| | 3rd | L2 | L2 | L2 | L2 | L2 | L2 |
| | 4th | L1 | L1 | L1 | L1 | L1 | L1 |
| | | Case 2 (minimum bidder is L2) | | | | | |
| | | A (L1 is the 2nd lowest bidder) | | | B (L3 is the 2nd lowest bidder) | | |
| | | ∅ | ∇ | ϑ | ∅ | ∇ | ϑ |
| Ranking | 1st | L4 | L4 | L4 | L4 | L3 | L3 |
| | 2nd | L3 | L3 | L3 | L3 | L4 | L4 |
| | 3rd | L2 | L2 | L2 | L2 | L2 | L2 |
| | 4th | L1 | L1 | L1 | L1 | L1 | L1 |
| | | Case 3 (min minimum bidder is L3) | | | | | |
| | | A (L1 is the 2nd lowest bidder) | | | B (L2 is the lowest bidder) | | |
| | | ∅ | ∇ | ϑ | ∅ | ∇ | ϑ |
| Ranking | 1st | L3 | L3 | L3 | L3 | L3 | L3 |
| | 2nd | L4 | L4 | L4 | L4 | L4 | L4 |
| | 3rd | L2 | L2 | L2 | L2 | L2 | L2 |
| | 4th | L1 | L1 | L1 | L1 | L1 | L1 |
| 60/40 ratio | | Case 1 (minimum bidder is L1) | | | | | |
| | | A (L2 is the 2nd lowest bidder) | | | B (L3 is the 2nd lowest bidder) | | |
| | | ∅ | ∇ | ϑ | ∅ | ∇ | ϑ |
| Ranking | 1st | L4 | L4 | L4 | L4 | L3 | L3 |
| | 2nd | L3 | L3 | L3 | L3 | L4 | L4 |
| | 3rd | L2 | L2 | L2 | L2 | L2 | L2 |
| | 4th | L1 | L1 | L1 | L1 | L1 | L1 |
| | | Case 2 (minimum bidder is L2) | | | | | |
| | | A (L1 is the 2nd lowest bidder) | | | B (L3 is the 2nd lowest bidder) | | |
| | | ∅ | ∇ | ϑ | ∅ | ∇ | ϑ |
| Ranking | 1st | L4 | L4 | L3 | L4 | L3 | L3 |
| | 2nd | L3 | L3 | L4 | L3 | L4 | L4 |
| | 3rd | L2 | L2 | L2 | L2 | L2 | L2 |
| | 4th | L1 | L1 | L1 | L1 | L1 | L1 |

**Table 6** (continued)

| | | Case 3 (minimum bidder is L3) | | | | | |
|---|---|---|---|---|---|---|---|
| | | A (L1 is the 2nd lowest bidder) | | | B (L2 is the 2nd lowest bidder) | | |
| | | $\varnothing$ | $\nabla$ | $\vartheta$ | $\varnothing$ | $\nabla$ | $\vartheta$ |
| Ranking | 1st | L3 | L3 | L3 | L3 | L3 | L3 |
| | 2nd | L4 | L4 | L4 | L4 | L4 | L4 |
| | 3rd | L2 | L2 | L2 | L2 | L2 | L2 |
| | 4th | L1 | L1 | L1 | L1 | L1 | L1 |

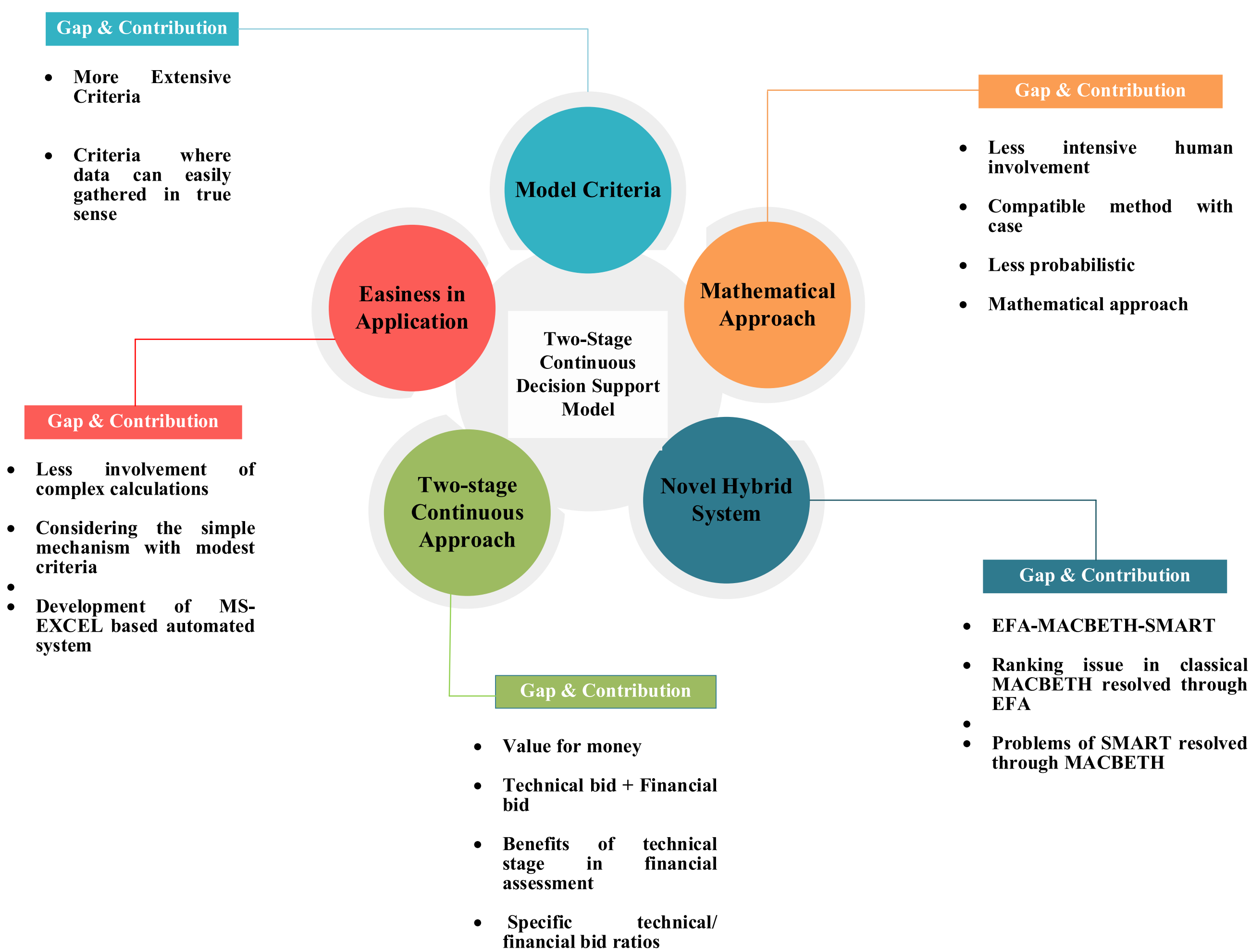



**Fig. 14** Comparative assessment of model

In addition to the model criteria, the second chief pillar of the contractor selection model is the employed methods to analyze the data in terms of decision-making techniques. The successful execution of a construction project is profoundly impacted by accomplishing the right decision during the selection process. In some cases, heavy reliance on human-based selection was adopted even after the inclusion of MCDM methods such as in (Hasnain et al. 2017; Semaan and Salem, 2017; Rao and Rathish 2018; Birjandi et al. 2019; Marcarelli and Nappi, 2019). This problem is worsened by choosing a technique that is incompatible with the case, for instance, an extremely larger pairwise comparison with the qualitative approach produces doubtful results when the model criteria are extensive likewise in AHP, ANP, and PROMETHEE. Apart from the aforementioned limitations in MCDM, the addition of higher probabilistic and larger hybrid methods adding further complexity for instance in the case of (Vahdani et al. 2013; Zavadskas et al. 2016; Hasnain et al. 2017; Taylan et al. 2017; Hashemi et al. 2018).

The proposed model developed a novel hybrid system based on the triplet combination of EFA-MACBETH-SMART. The hybrid system is proposed based on the limitations of MACBETH and SMART as a single method. MACBETH and SMART techniques have fundamental advantages over other MCDM techniques; nonetheless, the ranking problem of MACBETH and weightages calculations in SMART have remained unresolved. The said inherent issues in both techniques are resolved via a triplet combination which turns as EFA-MACBETH-SMART for the first time ever. Besides, the concept of two-stage models in contractor selection has been attempted by (San Cristóbal 2012; Liu et al. 2017; Cheaitou et al. 2019; Marcarelli and Nappi 2019; Zhao et al. 2019); however, these models operate under the principle of discrete approach, and continuous assessment has not been addressed. The present model principally operates under the continuous assessment system, which recognizes the prominence of technical assessment in the final stage and also retains the concept of value for money. This model proposes $R_{T/F}$ ratios where the client can choose a suitable ratio to evaluate contractors.

Various models in the past have developed that are not developed with the aim of easiness and simple procedures in their model so that those can easily be adopted in a real scenario. In contrast to this, overlapping and burdening of models with a complicated and large number of MCDM in a single case seems a common problem in past models. This is confirmed from the (Holt 2010) who reviewed the contractor selection models of two decades and concluded that the developed models are additionally complex, henceforth, are not suitable for the public sector. The term easiness in the application is directly linked with the above two terms, i.e. model criteria and mathematical approach, alongside with selection mechanism. In past models, the term hybrid methods have been presented with complex calculations. A large number of extremely complex MCDM methods in a single case is challenging to apply in a real case scenario, especially in the public sector where people believe in simple and straightforward processes such as in (Cheng and Kang 2012; Zavadskas et al. 2016; Borujeni and Gitinavard 2017). Moreover, the selection of contractors based on certain vague criteria such as time, risk, health, and safety, etc. with bid price creates further complexity in the models, for instance in the models by (Plebankiewicz 2012; Yang et al. 2012; Rao and Rathish 2018; Ye et al. 2018). A few models included bid price during the technical stage, such as (Watt et al. 2010; Yang et al. 2016; Semaan and Salem, 2017) and other models evaluated contractors without bid price i.e., (Nieto-Morote and Ruz-Vila 2012; Yang et al. 2016; Taylan et al. 2017; Tomczak and Jaśkowski 2018) which is in contrast to public sector regulations.

## 11 Conclusion

The present work aims to develop a novel automated two-stage continuous decision support model for contractors' assessment and selection. The idea of the discontinuous progression of the technical phase in the final selection stage in past models unrest the authors. Extensive model criteria were designed to assess the contractors based on the concept of Critical Criteria, Value-Added Criteria, and Desirable Criteria. The model criteria were initially ranked via Exploratory Factor Analysis (EFA) and later weightages were determined using MACBETH technique in M-MACBETH software. The exhaustive assessment of model criteria was performed using SMART technique which produced the performance grading assessment levels. Each contractor in the competition was assessed based on technical and financial bids. The model also preserves the concept of efficient use of public resources in addition to supporting the technically highest bidders. The idea of extensive contractor selection using an extensive criteria assessment system was kept under priority consideration. Furthermore, the concept of a simple and straightforward model that sounds practical on the ground was resolved using an automated assessment system which is another major contribution of this study. Hybrid novel combinations of decision-making techniques were implemented based on their true applicability. The inherent problem of ordinal data in MACBETH was resolved using EFA; moreover, the primary issue of computing weightages in SMART was resolved using MACBETH. This unique combination of EFA-MACBETH and MACBETH-SMART turns to EFA-MACBETH-SMART triplet-combination that resolves the inherent issues of decision-making methods. The findings obtained from the analysis of extensive model criteria suggests that 73 criteria (out of 76) are the most influential for assessing the contractor. The Critical Criteria category obtained the highest weightage of 50%, whereas, Value-Added Criteria and Desirable Criteria category attained 30%, and 20% weightage respectively. Study finds that the final selection of contractor can be performed on various technical bid/financial bid ratio ($R_{TF}$) such as 80/20; 75/25; 70/30; 65/35; and 60/40. A hypothetical case of contractors' assessment system tested on a few bid price assumptions such as $\varnothing$ = variations from 5 to 10% (5%, 7.5%, 10% respectively by each contractors), $\nabla$ = variations from 5to 15% (5%, 10%, 15% respectively by each contractors, and $\vartheta$ = variations from 5 to 20% (5%, 10%, 20% respectively by each contractors). The study concludes that in 80/20 $R_{TF}$ ratio, L4 contractor is always a winner, whereas, in other cases of $R_{TF}$ ratios, L3 contractor could also win the competition based on a few conditions described under Sect. 9.

The research supports that each contractor must be assessed individually based on their corresponding performance assessment level. The research further supports the idea that a contractor must be assessed continuously until the final selection stage, and technically high contractor which lies in higher performance levels must win the contractor if quotes a financial bid under the umbrella of a feasible bid. Furthermore, the higher benefits must be given to a high-level performer, and correspondingly more compensation is offered in quoting the bids other than the lowest price. The study thus concludes through a hypothetical case that a contractor with the highest technical bid score must win the award even if not being the lowest but proposed a feasible bid. Furthermore, research finds that the lowest bid contractor can also win a contract providing high technical assessment score.

## Appendix A:Preliminaries in MACBETH

Let S is a set of finite elements and ∀ i, j, k,l (∈S) is a subset of another number Q [∀ Q∈{0, 1, 2, 3, 4, 5, 6}]. To rank the criteria, the set S must satisfy Condition 1 of the linear programming from classical MACBETH.

Condition 1: [For ranking the criteria].

Say, i, j, k, l represent the four different judgments on a seven-point semantic scale of differences such that i is more attractive than j, and k is more attractive than l, then the first condition can be followed as;

$$\forall \text{ i, j, k, l} \in \text{S} : [\text{i is more attractive than j} \Leftrightarrow \text{i} > \text{j} \wedge \text{k is more attractive than l} \Leftrightarrow \text{k} > \text{l}] \tag{6}$$

e attractiveness can be found through semantic scale. Condition 1 in classical MACBETH satisfies through direct rating or swing weight method where the fundamental intention is to rank the criteria in decreasing order. This represents the ordinal information (ranking the criteria) from the DMs. However, the process of MACBETH is based on the assumption of converting the ordinal information into cardinal information (based on differences of attractiveness). This conversion can be satisfied by following Condition 2 of linear programming of MACBETH.

Condition 2 (i): [Relation as measure of attractiveness between two elements].

From Condition 1 we have the information about the order of criteria and say ∀ (i, j) ⇔ (k, l)∈Q (here Q denotes the measure of difference of attractiveness), then;

$$\forall \text{ i, j, k, l} \in \text{S} : [\text{iQj} \Leftrightarrow \text{u(i)} > \text{u(j)} \wedge \text{kQl} \Leftrightarrow \text{u(k)} > \text{u(l)}] \tag{7}$$

Condition 2 (ii): [quantifying the level of attractiveness]

$$\forall \text{ i, j, k, l} \in \text{S} : \text{(i, j)} \wedge \text{(k,l)} \in \text{Q} : [\text{u(i)} - \text{u(j)}]/[\text{u(k)} - \text{u(l)}] \tag{8}$$

Further,

$$i <^{Q_i} j \tag{9}$$

$$k <^{Q_i} l \tag{10}$$

Eq. A4 and A5 describe the relation between elements such as i and j, and k and l respectively on the scale of Q such that j is Q times greater than i, and l is Q times greater than k. At the scale Q, if i is strongly attractive than j and similarly, k is extremely attractive than l; equation A4 and equation A5 turns to equation A6 and A7 respectively.

$$u(i) - u(j) = 5\cap \tag{11}$$

$$u(k) - u(l) = 6\cap \tag{12}$$

∀,∩ must meet the necessary condition say u(i), u(j), u(k), u(l)∈[0,100].

Applying the Condition 1 and Condition 2 and solving the equation A6 and A7, the following additive value model would generate as mentioned in equation A8 and A9.

$$U(S) = \sum_{m=1}^{n} \left(w_m\right)\left(u_m\right) \tag{13}$$

$$\sum_{m}^{n} w_m = 1 > 0 \tag{14}$$

## Appendix B:Preliminaries in SMART

SMART likewise MACBETH operates on the elementary principle of additive value model. The utility values in SMART can be calculated by multiplying the criteria weightage with their expected utility values. Hence the earliest step is to develop objective weightages. The weightage ($w_\alpha$) can be calculated by the normalization process using Eq. B1. The normalization process produces the final criteria weightage, later on, the criteria value (performance values) ($V_{ak}$) can be computed.

$$V_{ak} = \sum_{\alpha=i}^{\beta} \left(w_\alpha\right) * \left(V_k\right) \tag{15}$$

The utility value of each criterion can be calculated using Eq. B2, the value is normalized on a scale of 0–1.

$$V_k = \frac{\Delta\alpha\beta - \Delta min}{\Delta max - \Delta min} \quad (16)$$

where; $w_\alpha$ is the relative weightage of each criteria/sub-criteria (from 1 to 100). $V_k$ is the utility value of each criteria/sub-criteria [0 to 1 scale; 1 = highest, 0 = lowest]. $\Delta min$ is the minimum scale value. $\Delta max$ is the highest scale value.

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**Data availability** The required data will be provided upon request.

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## Declarations

**Conflict of interest** The authors declare that there is no conflict and competing interest with any individual or any organization while exploring and writing this research.

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