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Decision-support modelling tool for contractor-to-project assignment and project management

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Abstract: A project's success or failure can be attributed to various management factors, including consistency or discrepancy in decision-making. The degree of inconsistency, lack of expertise, comprehension, or ignorance in some cases are just a few of the many variables that might impact the process's consistency and result in poor decision-making. Techniques have been developed to aid in consistent decision-making, but the selection process became extensive and disallowed wide adoption of such techniques in construction and project management practice. As such, a project-to-contractor assignment problem is one of the important areas in which a slight mistake leads to notable losses. Therefore, there is a need for better decision-support tool development. This study introduces Analytical Hierarchy Process (AHP)-based development and application of a management science technique along with game-theoretic modelling to develop a decision-support tool, successful project management (SPM), to assess and lessen the impact of human inconsistency on construction projects to contractor assignment and management decision-making. It is demonstrated that contractor preferences can be used to assign projects to contractors. The developed method significantly reduces managers' effort to make informed decisions for successful project completion. Case studies are presented to demonstrate the improvement in AHP and efficiency of the proposed method, along with precise results and comparisons for the effort one would need to complete the process successfully. Sample problems demonstrate the use of traditional AHP and then the application of the proposed technique to highlight the improvement. As demonstrated, time savings to arrive at consistent decisions are multi-fold.

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1 Introduction

Every portfolio manager or project manager wants to see a portfolio or particular project through to a successful conclusion. It is notable that this applies to all industries. As stated in the technical and non-technical sections of contracts, the chief goal of project management is to complete all projects on time, within budget, and to a suitable quality standard. Unfortunately, this goal is not always attainable, even if it is highly desirable. It is frequently thought that limited communication, a lack of understanding of the project's requirements and scope, the owners' skewed expectations, and other issues are to blame for project failures. These factors can determine whether a project succeeds or fails, although some projects never come to completion even when the abovementioned factors are present. It is notable that the decision-makers' lack of soft skills such as communication, employee engagement, employee motivation, and stakeholder management is the reason for the failure (Kantata 2024).

On the contrary, one may argue that project failure can be attributed to non-cooperative behaviour by all parties involved. Is it the operating environment that offers a protective shield for risks, or is it acceptable to think that the exercising of authority or overconfidence could contribute to poor decision-making? More often, a project or portfolio management did not consider human bias or process inconsistencies. Human inconsistency as a factor could mean different things depending on how it is defined. For example, the user cannot be held accountable for failure if they mishandle a machine or product because there was a flow present in the assignment process from the beginning. Then, to reduce the possibility of failure in the future, the decision-maker would have to go above and beyond to identify and improve the procedure. If there are no conflicting opinions and the decision-making team is productive, there is a greater chance of a good outcome.

If this is not the case, those in positions of power will usually oversee the necessary corrective action. To tackle the problem impartially, the best course of action would have entailed considering and evaluating each proposed remedy (Spalek 2005). Each suggestion brought up a feature to consider before selecting. Can this approach be used to assign and manage projects and portfolios more effectively? If so, how would one go about doing so?

2 Literature review

Many researchers in the area of construction industry (Moore 1985; Nguyen 1985; Aitah 1988; Russell and Skibniewski 1988; Russell 1990; Al-Alawi 1991; Skibniewski and Chao 1992; Al-Ghobali 1994) have described the importance of considering the human factor – bias or inconsistency – in the decision-making process. Human bias or inconsistency has long been a research topic. Most of the research on this topic was done from a human psychology standpoint to predict particular behaviours or results. These actions could and will affect the project's finances favourably or unfavourably. Similar decision-making concepts can be seen in both the management and economics fields. Many project and portfolio management decisions impact individual initiatives' economics. As a result, some studies have examined how people behave when they anticipate particular results. According to research on supply chain management (SCM) by Carter et al. (2007), humans may struggle to evaluate and estimate probabilities or create projections to deal with unpredictable scenarios. Other studies yielded similar results (Fischhoff 1982; Hogarth 1987; Thaler 2000). More than 60 years ago, Simon (1957, p. 198) stated that the human mind's capacity for formulating and solving complex problems is minimal compared to the size of the problems. When a solution is required for objectively rational behaviour in the real world, such an outcome is needed even for a reasonable approximation to such objective rationality. While artificial intelligence (AI) is undoubtedly capable of performing numerous analyses in a matter of milliseconds these days, the tools necessary to support managerial decisions daily – or to the extent necessary for managers to be able to rely on AI recommendations – confidently do not yet exist (Martela and Luoma 2021; Stadler and Reeves 2023).

Numerous investigations as depicted below were conducted from economic theory and human psychology perspectives, enabling an expectation of human decision-making closer to reality. Economists concur that shifts in an individual's irrationality do not always conflict with the results of forecasts made by conventional economic models, which assume that all parties are perfectly rational (Fama 1970). The rationale behind such an expectation is clarified by the possibility of random individual aberrations that people may experience when making decisions. Even though these outcomes would have been ideal, it has been demonstrated that decision biases exhibit more systematic patterns (Einhorn and Hogarth 1981; Kahneman et al. 1982). However, a popular theory explains that people still learn from their mistakes even when not making logical decisions. The same researcher also argues that, eventually, all rational acts will drive all irrational participants out of the market. However, this argument may not hold water because it is impossible to guarantee that the number of irrational participants in the industry will remain the same (DeLong et al. 1991). Tversky and Kahneman (1986, p. 252) noted that behavioural deviations from decision-making models are 'too widespread to be ignored, too systematic to be dismissed as random error, and too fundamental to be accommodated by relaxing the normative model'. According to Anderson (1970) and Hammond et al. (1975), there are notable variations in the consistency of human logical thinking compared to the outcomes of the well-developed decision theory analysis. Various computer models have been created and utilised to demonstrate how the human brain processes information and illustrate the impact of varying information sources on the final decision-making process (Wallsten and Barton 1982; Wilkening and Anderson 1982). Any decision-maker can use as many different strategies as they like to complete the cost-benefit analysis that will result in a final choice, according to Payne (1982).

There is proof that managers make biased decisions in the fields of business and management, finance (Shefrin 2000; Shiller 2003), marketing (Nicosia and Wind 1977; Backhaus and Koch 1985), and accounting (Colville 1981; Birnberg and Shields 1989). Regular departures from expected rational model assumptions occur. According to Beach and Connolly (2005), studying these biases is 'the psychology of decision-making'. In industrial and organisational psychology and management, it is also known as 'judgement and decision-making' (Yates 1990).

Studies to observe human decision-making consistency conducted for the armed forces verify that people react differently under different strain and stress situations. People react differently to the same amount of pressure, risk, and thought processes. However, most intriguing finding is that individual differences in these domains lead to bias. Human decision-making skills have been demonstrated to improve in such settings; as a result, detailed evaluation and the capacity to respond to it in various situations enhance overall and reduce decision bias (Cannon-Bowers and Sales, 1998). Even with training, some people behave inconsistently in high-pressure situations, which are common in projects. Humans frequently rely on heuristic analysis and approach to help identify a potential course of action or make a decision to make sensible decisions. A decision-makers' experience is typically the foundation of heuristic techniques (Jullisson et al. 2005; Shah and Oppenheimer 2008; Dietrich 2010). A method aiding to reduce the impact of decision inconsistency in the process was identified by carefully examining previous studies. Compared to more conventional heuristic approaches, it can be completed more systematically. One can achieve such results by analysing potential decision-makers' preferences about a project-specific evaluation and assessment, which increases the possibility of consistent decision-making. Our suggested methodology can be used at any point to support well-informed decision-making throughout a project assignment or even development. The conceptual approach for comparing the attributes for importance as in our modified AHP and application of game theory is the foundations of our innovative tool development presented as successful project management (SPM) technique. The methodology below describes the steps and details of the developed SPM technique (Avetisyan, 2021).

3 History, theory, and procedure of AHP and game theory

3.1 AHP

To aid in the decision-making process with consistency, Saaty (1994a, 1994b) developed the AHP in the 1970s. The AHP is a research method belonging to the category of multi-criteria decision-making (MCDM) methods. AHP aids in making complex and non-intuitive decisions by breaking the problem down to hierarchy consisting of more comprehensible set of sub-problems. Saaty (1994a, 1994b) simplified complex decision-making processes by combining psychological and mathematical ideas in a single context. In situations where a basic heuristic or other sophisticated approach would not be able to yield the optimum result, the application of the AHP enables the selection of the optimal alternative among multiple opportunities. Pairwise attribute comparisons made by decision-makers can be verified for bias or inconsistency using AHP, facilitating more precise selection or decision-making. To proceed further, the decision-maker must amend their relative preference assessment and reconsider their consistency. Although the procedure was improved over time, the computationally difficult and time-consuming procedure at its core still discourages managers from embracing AHP.

More details about the procedures, including how AHP was developed, can be found in the study by Saaty (1994a, 1994b). Initially developed by Thomas Saaty in the 1970s, AHP was not in its current state, and the development continued for further fine-tuning of the method. Thomas Saaty introduced AHP while working at the Arms Control and Disarmament Agency in the U.S. State Department. He aimed to quantify intangible factors in decision-making processes (Saaty 2017). The first formal record of AHP use was recorded in a report for the Logistics Management Institute in 1972. It was used to prioritise the war reserve stock.

Saaty further expanded the application of AHP by publishing foundational books and journal papers, introducing the application of the method. The publication of 'The Analytic Hierarchy Process' (1980) formalised the methodology and its applications (Saaty 2017). From the 1990s to the 2000s, AHP gained much broader acceptance in business, government, and healthcare industries. It helped with problems such as resource allocation, policy analysis, development, and strategic planning (SixSigma 2025). AHP has been combined with other decision-support frameworks, such as the analytic network process (ANP) or fuzzy logic, allowing it to handle complex problems that decision-makers face (Tavana et al. 2023). Chaube et al. (2024) presented an extensive overview of the history and development of the AHP method.

The theoretical background of AHP is based on the decision-maker's ability to consistently assign weights to the attributes that should be used in the MCDM process within acceptable proximity versus ideal consistency. Since this method combines psychology and mathematics, approximate accuracy allows the decision-maker to have some level of inconsistency, which later gets checked and verified for accuracy. However, it is documented that due to the need for reasonable consistency, the application of AHP can be challenging, especially in instances when the user is unfamiliar with the method and its potential (Emrouznejad and Marra 2017; Tavana et al. 2023).

AHP has a formal procedure that starts with defining the problem and setting the goal, then structuring the hierarchy, pairwise comparisons, calculation of weights, and synthesising the results.

The theoretical basis of AHP is based on three principles:

1. Decomposition: The problem is broken down into a hierarchy of more easily comprehended sub-problems at this stage. This is done so that each sub-problem can now be analysed independently.
2. Comparative judgements: At this stage, the hierarchy elements are evaluated by comparing two elements using a time approach. This allows us to understand their impact on each other in the hierarchy structure. At this step, the decision-maker uses specific data combined with human judgement.
3. Synthesis of priorities: At this stage, the decision-maker converts evaluations to specific numerical values that can be processed and compared throughout the problem range. This step allows the derivation of numerical weights and priorities for each element in the hierarchy.

Specific steps in the AHP process are presented below under the “Sample problems/case studies” section.

3.2 Game theory

The theory of game theory consists of creating mathematical models allowing analysis of the behaviour or response of other participants resulting from the moves of the opponent party. Key features of the process are the players, strategies, payoffs, and the equilibrium from which no player wants to deviate. Players are the participants of a game where they can exercise their strategies as possible actions, resulting in payoffs as outcomes that can be evaluated from the combination of the chosen strategies. Eventually, the goal is to get into an equilibrium state where no player wants to deviate from their chosen strategy.

The most famous equilibrium concept is the Nash Equilibrium, introduced by John Nash (Başar 2021). The development of game theory took a reasonable amount of time, from its initial mention in the works of mathematicians Emile Borel and John von Neumann. It was initially mentioned in 1928 in a paper on the theory of games. Later, it was further developed and advanced by John von Neumann and Oskar Morgenstern. In 1944, they published ‘Theory of Games and Economic Behavior’ and applied it to study economics. The development of game theory continued in the 1950s, and it was then that John Nash introduced the Nash Equilibrium along with cooperative game principles. Later, in the 1970s, the foundation of evolutionary game theory was laid by John Maynard Smith, who applied it to biology problems. Since then, the application of game theory found its place in many areas, including government and private sectors, for strategising policies, business decisions, and more (Başar 2021).

3.3 Research objectives and output

The research objective of this work is to provide a technique that serves as a tool aiding in the decision-making process when selecting contractors for projects and making efficient decisions for managing those projects. While the use of AHP in the construction industry or project-to-contractor assignment setting is not a novelty (Moore 1985; Nguyen 1985; Aitah 1988; Russell and Skibniewski 1988; Russell 1990, 1991; Al-Alawi 1991; Skibniewski and Chao 1992; Al-Ghobali 1994), our developed approach SPM brings the novelty by eliminating the complex process of AHP consistency checks and iterations, yet allowing realistic value considerations in the decision-making process. Most importantly, the project assignment to a contractor using our method depends on identified priorities and values that are communicated by the contractors and is not based on referrals and other traditional evaluations of contractors. This approach allows contractors to identify their strong skills and express their preferences for different projects.

4 Methodology

To demonstrate the SPM technique, we start with illustration of inefficiency of AHPs and then showcase our developed approach as an improvement that shows the technique’s effectiveness.

The trouble is that applying AHP to construction management decision-making daily involves time-consuming assessment processes and ascertaining the relative relevance values of characteristics or qualities employed in pairwise comparisons. For example, if someone had to decide which project to go with or out of few solutions which one to select and there were just five factors of comparison to consider using the standard AHP method, the manager would have to select the importance values for a five-by-five comparison matrix. In this simple example, selecting 25 relative values for importance expression and keeping consistency in those choices without using any technique is challenging. The sample problems presented below indicates how the traditional AHP application looks like that is followed with SPM technique. The theoretical basis of applying AHP for a contractor to a project assignment can be seen at a meso level, concentrating at an organisational or a specific community level for analysis of a social phenomenon (Little 2023). On the contrary, game theory used in sequence of the AHP improvement procedure primarily belongs to the field of applied mathematics while being extensively used in economics, social sciences, logic, systems science, and computer science. The use of game-theoretic modelling at the problem level allows to select participant that can strategise and maximise their success rate. Game-theoretic models have been widely used in instances where the user may not be able to find the clear and distinct values.

4.1 SPM method/approach

As described above and depicted below under the "Sample problems/case studies" section, the application of traditional AHP consists of formal steps that the decision-maker needs to follow, starting with the attribute selection for comparison. Once the attributes are selected, the decision-maker needs to identify the weights of the attributes compared to each other. Then, the comparison must be consistent among all attribute comparisons or within an acceptable range for the final results to be acceptable. Once the attribute comparison is consistent, the decision-maker needs to compare different options of a subject matter per attribute and again stay consistent. This is where the AHP can become not so user-friendly, and decision-makers may not find the perfect values to provide consistency at all levels. Figure 1 illustrates the AHP as a hierarchy structure.

The decision-making process as a flowchart using traditional AHP is depicted in Figure 2.

Although a seemingly straightforward process, applying AHP has complications that other researchers have previously documented. As such, the rank reversal, subjectivity in pairwise comparisons, scalability issues, assumption of independence of attributes, and difficulty related to qualitative to quantitative conversions are known shortcomings for adopting AHP and require decision-makers close attention to arrive at a reasonable and reliable selection (Karthikeyan et al. 2021; Munier and Hontoria 2021).

The flowchart of using SPM is depicted in Figure 3, where the decision-maker needs to decide on attributes and then compare one attribute to other attributes. The rest of the calculations will be completed in automated mode by perfectly meeting the consistency requirements and by eliminating the need for hectic iterations just to match values for consistency. More importantly, the decision-maker selects the attribute weight values based on best, worst, and most likely values, as in real life, where a precise number may not readily be available or even attainable. It is important to note that the hierarchical structure for SPM is the same as depicted in Figure 1.

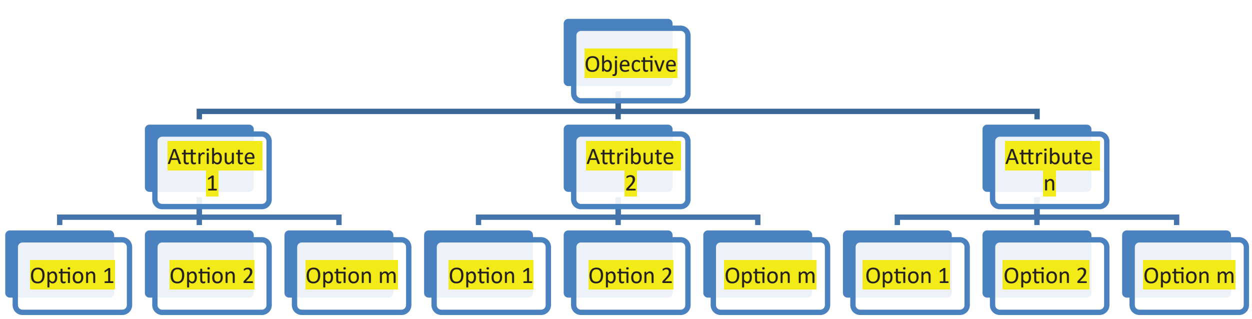

Fig. 1: Hierarchy structure for AHP.

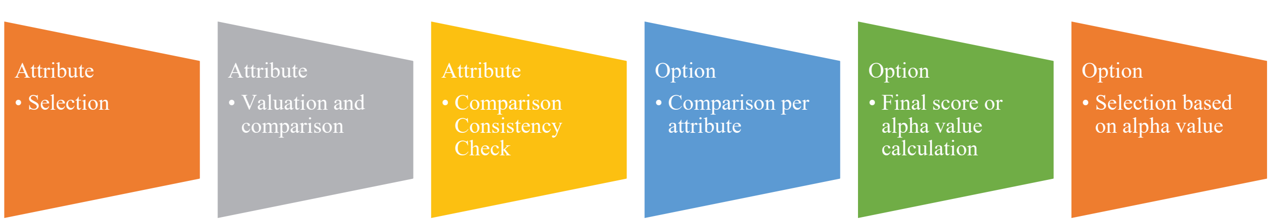

Fig. 2: Flowchart of using traditional AHP.

Fig. 3: Flowchart of using SPM and game-theoretic selection. SPM, successful project management.

The application of the process is demonstrated in the following section through different case studies.

5 Sample problems/case studies

Sample problems below illustrate the application and usefulness of the developed technique.

5.1 Owner's representative

In the following example, we analyse owner's representative who chooses projects for the owner experienced in development projects. The goal is to choose the best project, and in order to do this, the selection process needs to employ a reliable approach that upholds consistency in project assessment. The decision-maker is in a position to decide the project comparison criteria and figure out which project best fits the needs of the business. It is agreed that the attributes will be:

A – the potential for stakeholder;
B – the potential for profit generation;
C – the potential for technical feasibility;
D – the potential for early completion; and
E – the potential for immediate resource availability.

If the decision-maker relies on AHP, he or she must rank each attribute's significance compared to other attributes and then compare projects based on the discovered attributes using AHP. For instance, the decision-maker may weigh 'the potential for early completion' characteristics less important than 'the potential for stakeholder satisfaction'. The relative importance of each conceivable combination of attributes must also be determined; this evaluation should be expressed in values between 1 and 9, where 1 denotes equal priority and 9 denotes expressed differences in preferences. The decision-maker would have to go back to their selections of relative values of importance and make adjustments as many times as necessary to reach acceptable consistency if they failed to maintain consistency in determining the relative values for importance of attributes (within the acceptable range as specified in the original AHP method). This is precisely the point at which the trial-and-error method can become complicated, time-consuming, or occasionally impossible. Such a procedure may also lead to a heuristic approach or other workable possibilities preferred by decision-makers, but it may ultimately lead to an inaccurate decision and leave better options unexplored. In accordance with the above sample problem description, Table 1 offers potential data in a pairwise comparison matrix that an AHP method follower could generate.

The attribute pairwise comparison matrix M is the traditional name for the attribute comparison Table 1. It is clear from Table 1 that the pairwise comparison matrix's diagonal elements are all one. Since this property is the attribute's comparison to itself, it will always exist. On the contrary, the decision-maker should determine all other values in that matrix. Accordingly, the decision-maker significantly prefers 'the potential of stakeholder satisfaction' characteristic above 'the potential for profit generation', as shown by rows A and B. Likewise, attribute D over B is equal to one, indicating equal importance, as can be seen by looking at the numbers in the matrix.

In contrast, it is notable that the decision-maker indicated that trait B over D is considerably essential with a value of seven. This may be seen by closely examining other numbers. This matrix has numerous inconsistencies when all the integers are checked for pairwise comparison. The following is a summary of how to use AHP calculations.

Tab. 1: AHP attribute pairwise comparison table also presented as a matrix *M* for calculations.

Attributes	A	B	C	D	E
A	1.00	7.00	6.00	5.00	3.00
B	3.00	1.00	5.00	7.00	4.00
C	2.00	0.20	1.00	3.00	1.00
D	0.20	1.00	0.30	1.00	0.30
E	0.20	0.20	1.00	4.00	1.00

Step 1: Make the decision-maker's initial pairwise comparison matrix M normalised or scaled such that the sum of its columns equals 1.
Step 2: Estimate the decision-maker's weights w_i by calculating the approximation of w_{max}, which is the average of the entries in each row i of the normalised pairwise comparison matrix.

Four more steps are added to verify that the initial matrix M is consistent.

Step 1: Compute product Mw using original/unscaled M matrix, where w is a vector.
Step 2: Compute intermediate values as:

$$\text{Int.}v. = \frac{1}{n}\sum_{n=1}^{i} \frac{i^{\text{th}} \text{ entry in } Mw}{i^{\text{th}} \text{ entry in } w}$$

Step 3: Compute the consistency index:

$$\text{CI} = \frac{\left(\left(\text{Int.}v.\right) - n\right)}{n-1}$$

Step 4: For the right value of n, where n is the number of attributes covered above, compare the consistency index (CI) with the random index (RI). When a decision-maker is entirely consistent, $Mw = n$ and CI = 0 are the outcomes.

If the ratio of the CI to the RI is <0.1, the decision-maker is still consistent according to the AHP technique; if the value is more significant than 0.1, the decision-maker has to review their selections of the relative priority values for the qualities. After carrying out the above computation processes for the data in Table 1, the CI/RI equals 0.9024, indicating that the pairwise comparison matrix contains many inconsistencies.

It is possible to obtain an acceptable value that keeps the pairwise comparison matrix constant within an acceptable range after a lengthy process of trial-and-error, which in fact resulted in limited applications and adoption of traditional AHP. This is also the instance where SPM technique offers significant improvement, otherwise such pairwise comparisons are difficult to handle, even when using a record that must eventually be reviewed and modified. It is known that the better the time utilisation of a project manager, the more productive they can be on their own tasks, and therefore any such tool development can have a significant overall impact on time and quality management.

A part of the flexibility brought by SPM technique is the opportunity for the decision-maker to think of possible values as preferences instead of hard-set values in well-known traditional AHP methodology. It should be stressed out that the decision-maker may be more comfortable assigning values within ranges than precise values. This may be the case because an individual may be able to remember some of the best results that came from particular situations in the past projects. At the same time, the decision-maker may encounter some concerns and problems more frequently than others during management which again would put them in a situation for thinking of some values for prioritisation instead of a solid number. The first section of the SPM technique was developed by incorporating these concepts into the process of choosing or setting values for attributes. As a result, the decision-maker can specify the optimistic relative importance values for attributes in the pairwise comparison matrix using the SPM technique.

Similarly, the decision-maker must specify the most likely and pessimistic values. The estimated value is then determined by using the most accurate method possible, taking into account the manager's and decision-maker's level of experience and competence. For instance, the pairwise attribute comparison value of 7 for A's stakeholder satisfaction potential to B's profit-generating potential in Tables 1 and 2 is computed as $\frac{a+4m+b}{6}$, where a is optimistic, m is most likely, and b is pessimistic values of the decision-maker's evaluation based on experience or understanding. For this sample calculation, values for a, m, and b are given in Table 2.

In a matrix form, Table 1 is set to be as M.

$$M = \begin{bmatrix} 1.00 & 7.00 & 6.00 & 5.00 & 3.00 \\ 3.00 & 1.00 & 5.00 & 7.00 & 4.00 \\ 2.00 & 0.20 & 1.00 & 3.00 & 1.00 \\ 0.20 & 1.00 & 0.30 & 1.00 & 0.30 \\ 0.20 & 0.20 & 1.00 & 4.00 & 1.00 \end{bmatrix}.$$

Instead of choosing every possible combination of comparison attributes, the second part of the SPM technique lets the decision-maker define the most critical attribute and then compare other attributes by defining their preference levels about the most crucial attribute

Tab. 2: *a*, *m*, and *b* values to estimate comparison values for attribute A to B, C, and D.

a	*m*	*B*	Attributes ratio	Pairwise comparison value
5.00	7.00	9.00	A/B	7.00
5.00	6.00	7.00	A/C	6.00
4.00	5.00	6.00	A/D	5.00
1.00	3.00	5.00	A/E	3.00

(as can be seen in Table 2 for A to B, C, and D ratios). To obtain an entirely consistent pairwise comparison matrix, the SPM tool automates the ratio computations for other combinations and completes the remaining values. This eliminates the need for the decision-maker to use the trial-and-error method ever again. As a result, Table 3a data, which are now totally consistent, are obtained by applying the first two segments of the SPM approach to the data in Table 1, row A.

In a matrix form, it will be as the following.

$$M = \begin{bmatrix} 1.00 & 7.00 & 6.00 & 5.00 & 3.00 \\ 0.10 & 1.00 & 0.90 & 0.70 & 0.40 \\ 0.20 & 1.20 & 1.00 & 0.80 & 0.50 \\ 0.20 & 1.40 & 1.20 & 1.00 & 0.60 \\ 0.30 & 2.30 & 2.00 & 1.70 & 1.00 \end{bmatrix}$$

Rather than modifying the preferences until we reach the same or similarly acceptable values that ensure that the final selections are accurate, the remaining numbers are filled in by SPM calculations as the data from Table 2 define attribute pairwise comparison values regarding attribute A. The weights w_i can be calculated as the averages of each row in Table 3b after the matrix has been normalised.

As such, the following values are the result:

w_A	$=0.543$
w_B	$=0.078$
w_C	$=0.090$
w_D	$=0.109$
w_E	$=0.181$

The decision-maker can now move on to project-to-project comparison per defined attribute with this approach, as shown by the normalised comparison matrix, which has identical values for every column. Pairwise comparison of the attributes is entirely consistent. The SPM technique is also applicable in this process. The decision-maker must now assess the values of the initiatives they wish to contrast. After that, preferences are applied to those projects, such as the attribute comparison procedure, using the evaluation values as a guide. For attribute A, a pairwise comparison of projects by attribute is shown. Pairwise comparisons of projects according to other criteria are completed similarly. Table 4 shows how an attribute-based project comparison table appears.

In a matrix form, the values will be as follows:

$$M_A = \begin{bmatrix} 1.00 & 0.33 & 1.00 \\ 0.10 & 1.00 & 2.00 \\ 1.00 & 0.50 & 1.00 \end{bmatrix}$$

Tab. 3a: AHP attribute pairwise comparison with SPM setup.

Attributes	A	B	C	D	E
A	1.00	7.00	6.00	5.00	3.00
B	0.10	1.00	0.90	0.70	0.40
C	0.20	1.20	1.00	0.80	0.50
D	0.20	1.40	1.20	1.00	0.60
E	0.30	2.30	2.00	1.70	1.00

SPM, successful project management.

Tab. 3b: AHP attribute pairwise comparison normalised data with SPM setup.

Attributes	A	B	C	D	E
A	0.543	0.543	0.543	0.543	0.543
B	0.078	0.078	0.078	0.078	0.078
C	0.090	0.090	0.090	0.090	0.090
D	0.109	0.109	0.109	0.109	0.109
E	0.181	0.181	0.181	0.181	0.181

SPM, successful project management.

Tab. 4: Pairwise project-to-project comparison per attribute A.

Projects	1	2	3
1	1.00	0.33	1.00
2	0.10	1.00	2.00
3	1.00	0.50	1.00

Tab. 5: Normalised pairwise project-to-project comparison per attribute A.

Projects	1	2	3
1	0.20	0.180	0.250
2	0.60	0.550	0.500
3	0.20	0.270	0.250

After normalisation (Table 5), the weights of each project are computed following the same calculation steps as before.

Weights for project-to-project comparison for attribute A:

$$w_1 = 0.210$$

$$w_2 = 0.550$$

$$w_3 = 0.240$$

Similar calculations as the AHP are now completed for all other attributes, and the results are summarised in Table 6.

Table 6's weight values correspond to the weights displayed above for the pairwise comparison matrix of characteristics, and the columns represent the project-to-project comparison for each attribute. For every

Tab. 6: Final output from SPM.

Weights i/project J	0.543	0.078	0.090	0.109	0.181	Alpha
Project 1	0.210	0.120	0.500	0.630	0.620	0.349
Project 2	0.550	0.550	0.250	0.300	0.240	0.440
Project 3	0.240	0.330	0.250	0.070	0.140	0.211

SPM, successful project management.

Tab. 7: Contractor J's valuation of projects.

Project j	Alpha
Project 1	0.411
Project 2	0.340
Project 3	0.249

project, alpha values are determined as a weighted total. As an example, the alpha value for Project 1 is computed as follows: 0543 ∗ 0.21 + 0.078 ∗ 0.12 + 0.09 ∗ 0.5 + 0.109 ∗ 0.63 + 0.181 ∗ 0.62 = 0.349. Project 2 will have the highest final alpha score based on the data in Table 6, suggesting that it is the project the decision-maker should choose since it most closely matches their preferences for each feature. Project 3 will be the least desired project, while Project 1 will be the next best option.

Similarly, the SPM tool will assist the decision-maker in determining which course of action to take if the decision is to choose an action item rather than a project. By weighing each attribute's significance, the decision-maker can determine the crucial ones and proceed accordingly. Although decision-makers can use the previously mentioned procedure, decision-making becomes more complex when multiple people are engaged. Therefore, SPM provides information for game-theoretic analysis in these kinds of scenarios. Consequently, applying game theory is the next stage in the SPM technique. The objective is to use game theory tools to get to a decision point in talks or negotiations that the parties concerned would want to stay on and to arrive at a mutually agreeable agreement as a point of equilibrium. Project management talks can depict a party's gain as another's loss since they resemble a non-cooperative game from a game theory standpoint. Gain and loss can be interpreted as a revenue and cost relationship in which the contractor receives payment, but the client bears the same financial burden. Similar scenarios can be examined when several contractors are vying for the same projects in a portfolio or when a contractor assesses a project's potential while considering its rivals' anticipated attribute valuations. SPM provides for studying human inconsistency at even more advanced levels of the decision-making process, complementing game-theoretic analysis for managerial decisions. As a result, the following scenario demonstrates how to apply SPM that serves as an input for game-theoretic analysis. The owner's representative of the developer plans to announce the bid by anticipating that the possible prime contractors (K and J) will be bidding. The owner's representative sets a plan for portfolio, and it has few projects that can be awarded simultaneously. Let us assume that not all projects can be funded because of resource constraints, but stakeholders said that, considering the scale of the projects, they would be able to support two of the three total projects at a time. Assuming that one of the contractors (Contractor K) has their preferences per project as the calculated values for the owner's representative case, the values as demonstrated above can be used in the following case discussion. Yet, to complete the process, there is a need for similar analysis for Contractor J. Assuming the analysis resulted in the values presented in this study given in Table 7, it allows to quickly show the next steps. Then, with such conditioning, Contractor K will preferably concentrate all estimation efforts and focus on winning Project 1. Recall that the calculation steps for Contractor J would be the same as those for Contractor K above. In a zero-sum competition, one contractor's victory can be seen as the competitor's loss. The developer may grant contractors access to the predefined attributes and request contractors to provide pairwise comparisons with their bids to use the SPM-supported game-theoretic technique. This would be a very beneficial input and a new technique for evaluation and selection in the construction industry. The developer can then decide how to assign the projects to the contractors. We can also examine the possibility that, in some circumstances, both prime and subcontractors will wind up working on the same project to pique the interest of the analysis further. In such a scenario, we can examine the potential reward for each contractor.

As such, let us now imagine that Contractors K and J have worked together on projects in the past and that, if agreed upon, they would want to work together as prime and subcontractors on the same project. They can hire one another as subcontractor if they successfully get funding for their dream project. This implies that if any of the projects are funded, each of these contractors may still benefit to some degree (this last part where contractors can collaborate just indicates that both can benefit and strategise to get projects which can be omitted entirely if desired). To utilise the game-theoretic technique, Table 8's payoff matrix is set. Table 8's numbers originate from alpha values (Tables 6 and 7) that Prime Contractors K and J acquired.

Tab. 8: Contractors K and J payoff data.

		J		
K	Alpha values	Project 1	Project 2	Project 3
	Project 1	0.349/0.411	0.349/0.340	0.349/0.249
	Project 2	0.440/0.411	0.440/0.340	0.440/0.249
	Project 3	0.211/0.411	0.211/0.340	0.211/0.249

Tab. 9: Contractors K and J reduced payoff data.

		J	
K	Alpha values	Project 1	Project 2
	Project 1	0.349/0.411	0.349/0.340
	Project 2	0.440/0.411	0.440/0.340

The payoff data, viewed through game theory, permit prospective prime contractors to modify their tactics. In practice, there is no way that the decision-maker may assign an identical assignment to both primes as an acceptable solution. The results from the payoff data show that neither K nor J finds Project 3 to be desirable. Consequently, Table 9 will be the only payoff data remaining.

Projects 1 and 2 may be chosen after examining the data in Table 9 and considering the announcement made to stakeholders on funding two initiatives. The next issue would be how to strategically plan the next stages at this point and who receives which project. It would be wise for the developer to consider the alpha value pairings in Table 9 and their bids to optimise the likelihood of those projects being completed successfully. Two possibilities in Table 9 will be removed because Contractor K or Contractor J can be allocated to either Project 1 or Project 2. The values in the diagonal will, therefore, be removed. The only option would be to check if Project 1 or 2 goes to Contractor K or J or vice versa.

5.2 Public works projects

In this example, decision-maker needs to consider three public works projects where three different contactors bid for all three projects. This approach does not limit the scenario where some contractors may bid for part of the projects instead of all projects. In this scenario, we consider that all three contractors qualify to bid for all three projects. While in this case the payoff matrix for each contractor is much larger, the conceptual approach is the same.

For the sake of eliminating repetition of steps in this case study, the calculations involving application of the first steps of SPM technique in accordance to the AHP are omitted. We simply show it as already decided and perfectly consistent table/matrix as an input. We highlight the application of the game-theoretic step of SPM application for contractor-to-project assignment with three participants/contractors given their expressed preferences like the above-discussed example.

As such, we have Contractors A, B, and C who bid for projects 1, 2, and 3.

Let us assume Contractor A's payoff matrix is:

Tab. 10: Contractor A's valuation of projects.

Project J	Alpha
Project 1	0.45
Project 2	0.27
Project 3	0.28

Likewise, contractor B's payoff matrix is given as:

Tab. 11: Contractor B's valuation of projects.

Project J	Alpha
Project 1	0.37
Project 2	0.52
Project 3	0.11

Similarly for contractor C we got:

Tab. 12: Contractor C's valuation of projects.

Project J	Alpha
Project 1	0.18
Project 2	0.41
Project 3	0.41

While numbers from Tables 10–12 can provide a hint on how to allocate the projects among contractors, the more organised approach would make it structured and reliable. To show these numbers collectively for all three contractors, we will use a table/matrix format with three entries in each cell (Table 13) consistent with game theory applications.

Table 13 should be interpreted according to the following approach. Project 1 row to Project 1 column intercept indicates that Contractor A has an alpha value of 0.45 for Project 1 if both Contractors B and C also select Project 1, Contractor B has an alpha value of 0.37, and Contractor C has an alpha value of 0.18 like Contractor A. Contractor C's choices are simply added as third element as it is done in game theory models for interpretation of the third player (or more) in the game. Similarly, Project 2 row to Project 1 column intercept indicates that Contractor A has selected

Tab. 13: Contractors A, B, and C (third number under each project) payoff data per project.

A	Alpha values	B Project 1	Project 2	Project 3
	Project 1	0.45/0.37/0.18	0.45/0.52/0.41	0.45/0.11/0.41
	Project 2	0.27/0.37/0.18	0.27/0.52/0.41	0.27/0.11/0.41
	Project 3	0.28/0.37/0.18	0.28/0.52/0.41	0.28/0.11/0.41

Tab. 14: Contractors A, B, and C (third number under each project) payoff data per project.

A	Alpha values	B Project 1	Project 2
	Project 1	0.45/0.37/0.18	0.45/0.52/0.41
	Project 2	0.27/0.37/0.18	0.27/0.52/0.41

Project 2 while Contractors B and C still show their alpha values for Project 1. Both Contractors B and C still show their other project alpha values while Contractor A selected Project 2. In a similar way, the same Project 2 to Project 2 intercept shows all contractors' alpha values for Project 2.

The column with Project 2 has two rows underlined that show the non-inferior combination of alpha values for projects by Contractors A and B. As such, it is observed that for contractor A, the project with highest alpha value is 1, for Contractor B, it is Project 2. Since Contractor C is equally satisfied with Projects 2 and 3 with an alpha value of 0.41, it can be assigned to Project 3. The decision-maker can confidently assign projects to all three contractors according to their highest preferred values and maximise the success potential instead of a random assignment.

This case study can be further expanded to a case where there are three contractors and two projects. In such scenario, the comparison table/matrix will be as given in Table 14.

When there are more bidders than projects, the decision-maker can again select the contractors with the highest alpha values as in the first case scenario for contractors K and J. Such approach will increase the successful completion potential of projects and contractors' satisfaction and desire to do a better job. From Table 14, it can easily be concluded that since Contractor A has expressed preference for Project 1 with an alpha value of 0.45 and Contractor B has expressed preference for Project 2 with an alpha value of 0.52, the decision-maker can assign the projects accordingly. Yet, it is important to note that Contractor C has demonstrated preference with an alpha value of 0.41 for Project 2. If the decision attributes have been clearly and accurately communicated by contractors, the decision-maker will not have a doubt in selecting the contractor with a higher alpha value. In other instances where such confidence is absent, the decision-maker may not be able to confidently make the call. To help in such situations, the decision-maker may refer to either goal programming or multi-objective optimisation, which is the possible future expansion of this technique.

6 Limitations

The developed method/technique is widely applicable for many situations, but the limitation comes from game-theoretic setup perspective where a pure equilibrium may not be achieved as seen in the case with three contractors and three projects setup where the alpha value for Contractor C shows indifference between Projects 2 and 3 allowing an easy assignment of projects to contractors. This would have been a bit harder choice for a decision-maker if the alpha values would suggest a possible deviation from the best strategy. Even though the above limitation is present, it is not affecting the decision-maker to assign the projects to the best of their knowledge. This would have been an important issue if the method was used by the contractors to agree on a bidding strategy to work cooperatively with each other. In a non-cooperative game, there is a higher chance of not finding an equilibrium point making the players to deviate from their choices for bidding decisions with anticipation that the other contractor may deviate from their selection in order to maximise their payoff. Yet, this may not ever be a problem because the decision-maker is the one who sees all responses in one place, and others in the game may not strategise against one other.

Another limitation of the developed technique is the issue related to the number of players and projects under consideration. When the number of projects and contractors grow beyond the comprehendible level, it might be challenging for a decision-maker to stay consistent in setting up the payoff matrix. While it is listed as a limitation, it is mostly considered as a user issue because it is solely dependent on the ability of setting the payoff values and recognising its accuracy. Depending on how advanced the decision-maker is, the level of difficulty of setting up the payoff matrices will be a different experience from one person to another. At the same time, in most of the cases, if prequalification of contractors is communicated accurately, there are almost always manageable numbers of contractors who want to bid for the set of projects.

7 Future work

Future expansion of this work is intended to help the decision-makers where the attributes may not have demonstrated differences. In such scenarios, decision-makers can use goal programming and multi-objective optimisation to find the entire Pareto frontier for comparison and then decide on possible allocation of the projects to contractors. With the use of goal programming, the decision-maker can use the alpha values to possibly maximise the total satisfaction level given all projects and their corresponding alpha values. This development is not part of this current work and will be presented in future as an extension of the presented technique/approach in this paper.

8 Conclusions

The improvement of traditional AHP as part of the SPM technique for consistency consideration of a decision-maker is a step forward to easy decision-making that can save time and effort at arriving to an accurate outcome without the need of multiple trial-and-error approaches. When the preference alpha values are decided, the decision-maker can use to assign projects to bidding contractors. For owner's representative problem, contractor J will be more inclined to support Project 1 if it is awarded the funding because it has a lower value than Project 2 (Table 9). Likewise, J believes that Project 2 is not as good as Project 1. Even if both projects were funded but assigned differently, their successful completion can be questioned. Yet with this assessment, both primes would be better off from their chosen position and able to deliver their best efforts. Both primes will still be assigned a project, but the outcomes will drastically differ. Similarly, in the case of public works projects, the decision-maker might be faced with situation where there are more than two contractors who want to bid for their projects and be able to make reasonable assignments of projects to contractors. The process is easy to follow and is consistent with game-theoretic payoff matrix set up. Table 13 summarises the payoff of all three contractors enabling exclusion of inferior options to leading options that allow assignment of projects to contractors based on their alpha values. In contrast, Table 14 summarises the case where there are less projects than contractors, and the decision-maker has a choice of picking only two out of three contractors. While the selection process of contractors is simplified with the developed technique, the limitations should be considered. It should be noted though that those are mostly or solely a user or application-related limitations, and the user can easily overcome the difficulties if they get some training.

The decision-making process would have been easier if solutions to several difficulties that would have enhanced the project's chances of success had they been considered, as previously stated, come up throughout project assignment, given the characteristics set for prioritising. The methodologies created for systematically analysing projects and portfolios with human preference considerations in the decision-making process might be used for all projects and programmes, and all parties participating in business strategy formulation could benefit from it. Overall, the developed technique SPM offers a significant benefit to decision-makers by aiding in staying consistent and assigning project to contractors or helping the owners and developers in their choices.

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