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A Hybrid MCDM Technique for Risk Management in Construction Projects

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Abstract: Multi-stakeholder based construction projects are subject to potential risk factors due to dynamic business environment and stakeholders' lack of knowledge. When solving project management tasks, it is necessary to quantify the main risk indicators of the projects. Managing these requires suitable risk mitigation strategies to evaluate and analyse their severity. The existence of information asymmetry also causes difficulties with achieving Pareto efficiency. Hence, to ensure balanced satisfaction of all participants, risk evaluation of these projects can be considered as an important part of the multi-criteria decision-making (MCDM) process. In real-life problems, evaluation of project risks is often uncertain and even incomplete, and the prevailing methodologies fail to handle such situations. To address the problem, this paper extends the analytical network process (ANP) methodology in the D numbers domain to handle three types of ambiguous information's, viz. complete, uncertain, and incomplete, and assesses the weight of risk criteria. The D numbers based approach overcomes the deficiencies of the exclusiveness hypothesis and completeness constraint of Dempster–Shafer (D–S) theory. Here, preference ratings of the decision matrix for each decision-maker are determined using a D numbers extended consistent fuzzy preference relation (D-CFPR). An extended multi-attributive border approximation area comparison (MABAC) method in D numbers is then developed to rank and select the best alternative risk response strategy. Finally, an illustrative example from construction sector is presented to check the feasibility of the proposed approach. For checking the reliability of alternative ranking, a comparative analysis is performed with different MCDM approaches in D numbers domain. Based on different criteria weights, a sensitivity analysis of obtained ranking of the hybrid D-ANP-MABAC model is performed to verify the robustness of the proposed method.

Keywords: D number; analytical network process (ANP); multi-attributive border approximation area comparison (MABAC); multi-criteria decision-making (MCDM); consistent fuzzy preference relation (CFPR); construction project risk; risk management

1. Introduction

In recent decades, projects in the construction sector have become more complex and risky due to the diverse nature of activities among global companies [1–8]. In comparison to other sectors, construction projects encounter more risks due to uncertainties occurring because of various construction practices, working conditions, mixed cultures and political conditions between host and home countries [9–12]. Thus, in this scenario, risk management can be considered a vital part of the decision-making process in construction projects. These projects may involve many stakeholders,

in addition to uncertain socio-economic conditions at the project site, bringing big challenges to practitioners of the industry in recent decades [13,14]. Construction project failure may cause higher costs and time over-runs, requiring a systematic risk assessment and evaluation procedure to classify and respond to changes [15,16].

Thus, prioritisation among construction based risk portfolios, and finding suitable risk mitigation strategies for construction projects, can be introduced as multi-criteria decision making (MCDM) problems. Researchers have recently proposed new methods for prioritising risks in construction based projects [10,17–19]. In addition, the increasing dynamism of construction projects has resulted in extensive impreciseness and subjectivities in this risk investigation procedure. With respect to the identification of risk criteria, a methodology is needed to sort and prioritise criteria weights, based on specific environments and domain experts' judgment. In the real world, since various uncertainties occur in the decision-making process due to subjective and qualitative judgment of decision-makers (DMs), so it is essential to develop a more optimised technique that can handle various types of uncertainties [15,20–24].

In this scenario, a proper decision-making methodology is required to solve multiple conflicting interdependent criteria when evaluating risks in construction projects. In recent years, the number of papers related to analytic hierarchy process (AHP) and analytic network process (ANP) methods, considering supplier selection procedure, has increased substantially [25–29]. However, increasing the number of criteria or comparison levels causes confusion in decision makers' (DMs) judgments, resulting in incomplete decision-making and inconsistency in the evaluator's judgments, thus reducing strategy selection ability. Under these circumstances, Herrera-Viedma et al. [30] proposed consistent fuzzy preference relations (CFPR) to evade inconsistency in the decision-making process, and thus models have been developed with CFPR structuring of the problem of multi-criteria knowledge based strategy selection both with AHP [31] and ANP [32,33]. The CFPR methodology requires less time, has computational simplicity, and also guarantees consistency of decision matrices. However, as CFPR is based on complete and certain information, there always exists a possible inconsistency risk due to the inability of DMs to deal with overcomplicated objects [34].

It is obvious that the approaches mentioned above can play a vital role under some special circumstances, but it also reveals more uncertainties due to the subjective judgment of experts' assessment. For fuzzy set theory it is difficult to determine in advance membership function values before making any decision in an uncertain and vague environment [8]. Interval theory has the same deficiency [23]. In addition, the frame of discernment and basic probability assignment (BPS) present in dempster–shafer (D–S) evidence theory limits its ability to represent incomplete information in uncertain situations [34,35]. In order to overcome the above shortcomings and effectively handle various uncertain and incomplete information, D numbers [36], a special kind of random set, is applied in the construction of CFPR. The D-CFPR [34] method expresses the expert's linguistic preference values using D numbers, and can also be converted to traditional CFPR. In recent years, papers related to D numbers based MCDM methods have begun to appear, viz. D numbers based vlse kriterijumska optimizacija i kompromisno resenje (D-VIKOR) [37], D number based grey relational projection (D-GRP) [38], D numbers based analytic hierarchy process (D-AHP) [39,40], D numbers based technique for order of preference by similarity to ideal solution (D-TOPSIS) [41], and D numbers based decision-making trial and evaluation laboratory (D-DEMATEL) [42].

Besides managing the various risks associated with construction projects, this study also attempts to categorise and assess their risk mitigation strategies, thus setting up a proper framework that is accountable to investors in the construction sector. Thus, a survey on risk mitigation strategies is performed, based on the recent works [9,23,43], to alleviate construction projects risks. Based on the above considerations, this paper also develops an extended version of the MABAC methodology in an uncertain and incomplete decision environment, in order to evaluate risk mitigation strategies in construction based projects. Some papers related to MABAC have been published in recent years, viz. traditional DEMATEL-MABAC [44], pythagorean fuzzy MABAC [45], interval type 2

fuzzy MABAC [46], interval-valued intuitionistic fuzzy MABAC [47], and the fuzzy AHP-MABAC model [48].

Thus, the key motivation of this paper is to develop a D numbers based ANP-MABAC decision-making methodology for prioritising construction project risks, and to find suitable mitigating strategies in uncertain and incomplete decision environments. In this paper, we choose the ANP methodology due to its ability to represent the potential interactions, interdependences, and feedback among the risk based criteria and sub-criteria. Hesamamiri et al. [33] developed a systematic framework combining ANP and CFPR to properly assess and select a knowledge management strategy.

In this paper, CFPR is taken into the decision matrix under D-ANP to find the priority vectors of the criteria for uncertain and incomplete environments. Thus, the main objectives of this research are as follows:

- Categorise and describe proper risk issues concerning various socio-economic, technical, and geo-political based sectors correlated to construction projects.
- Develop a logical structure incorporating a D-CFPR based ANP model for risk prioritisation during construction.
- Identify and prioritise risk response factors in the construction industry based on the D-MABAC methodology.

This paper is organised as follows: Section 2 offers an outline of construction projects along with a review of risk assessment in the sector. Section 3 briefly discusses the preliminaries of D–S evidence theory and D numbers theory, along with their properties. In Section 4, algorithmic methodologies of D-CFPR, D-ANP, and D-MABAC are discussed. Section 5 demonstrates the effectiveness of the above methodology by presenting a numerical example on risk prioritisation and responses in the construction sector. A discussion based on sensitivity analysis is given in Section 6. Finally, the conclusions and future direction of the present research are given in Section 7.

2. Risks in Construction Projects

2.1. An Overview

The construction industry in general, as well as individual construction projects, deals with various threats, which are called risks. Risk assessment in construction projects has been applied differently from project to project (using various models of risk assessment) to evaluate the risk in certain activities of the project [49]. However, the socio-economic complexity involved in construction events makes it more risk prone, so that there may be negative effects on project sustainability [23]. Due to various complex factors, the construction industry is highly diverse and heterogeneous, experiencing a great deal of dynamic change with global sourcing and increasing price competition [50].

To overcome these risks, contractors have generally used high mark-ups, but this approach is no longer effective, as their margins have become smaller [51]. In recent decades, the stages involved in construction projects have become far more complex in nature, due to technological upgrading and stakeholder pressure, and are characterised by a number of uncertainties, which have a negative influence on the projects [52]. As risk free construction projects are impossible in real life, a controlled risk assessment procedure is required to manage various risks in the projects. The aim of this study is to highlight the main risks that construction projects face and the risk mitigation strategies used to manage them.

2.2. Previous Studies on Risk Assessment in Construction Projects

There have been substantial developments over the last four decades in research related to construction project management. Projects have been considered that are either exposed to risks, or have apparently inherited risk due to the participation of several stakeholders (as owners, contractors and designers); see [53] among others. For classifying and managing risks effectively, many

methodologies have been suggested in the literature. In this section, a list of the existing approaches to construction project risk management is now briefly summarised.

Wang et al. [4] developed an alien eyes' risk (AER) model, categorising the project risks and their mutual relationships, and proposing a qualitative risk mitigation framework. Schieg [17] adopted a risk management process in construction project management, concentrating more on personal area risks. Zavadskas et al. [23] presented risk assessment based on the MCDM method and applying TOPSIS grey and grey number based complex proportional assessment (COPRAS-G). Wen [54] integrated rough sets and artificial neural networks (ANN) for risk evaluation of construction projects. Fouladgar et al. [55] proposed a risk evaluation outline faced during tunneling operations based on fuzzy TOPSIS methodology. Taroun and Yang [56] hybridised the dempster–shafer (D–S) theory of evidence and evidential reasoning algorithm for structuring personal experience and professional judgment with a spreadsheet-based decision support system. Mohammadi and Tavakolan [25] combined fuzzy logic and AHP in traditional failure mode effect analysis (FMEA) for construction project risk assessment. Serpella et al. [18] applied a knowledge-based approach, based on a three-fold arrangement and risk management function, to address project risks in the construction management sector. Ebrat and Ghodsi [14] identified the risks in construction projects based on the adaptive neuro fuzzy inference system and stepwise regression model for the evaluation of project risks. Taylan et al. [15] proposed hybrid methodologies combining fuzzy AHP and fuzzy TOPSIS and applied the relative importance index method to prioritise the project risks based on the data obtained. Iqbal et al. [9] considered two types of risk management technique during project execution, viz. preventive techniques (to manage risk before the start of the project) and remedial techniques (after occurrence of the risk). Vafadarnikjoo et al. [24] developed an intuitive fuzzy decision-making trial and evaluation laboratory (DEMATEL) to prioritise risks associated with construction projects by using the risk breakdown structure. Ahmadi et al. [27] analysed the criteria for prioritising potential risk events and quantified it using fuzzy AHP. The best response action for a risk event is then identified with respect to the same criteria using a scope expected deviation index. Santos and Jungles [19] evaluate the completion of construction project risk by considering the correlation of delay and the schedule performance index along with any time over-run. Shin et al. [28] made a comparative analysis of AHP and fuzzy AHP to evaluate the potential risk factors at the construction site of a nuclear power plant. Kao et al. [57] proposed an integrated fuzzy ANP based balanced scorecard system for evaluation of relevant bilateral factors in Taiwanese construction projects. Burcar Dunovic et al. [58] assessed large infrastructure projects by integrating the risk impact cumulative distribution curve based MCDM approach. Yousefi et al. [59] proposed a neural network model for predicting emerging time and cost claims applied to Iranian construction projects. Valipour et al. [60] presented a fuzzy cybernetic ANP model for proper identification of public-private partnership project based risks. Ulubeyli and Kazaz [61] developed a fuzzy based sub-contractor selection model (CoSMo) for global based construction projects. Rajakallio et al. [62] analysed the solution delivery from a network perspective in integrated business model renewal. For assessing risk in deep foundation excavation, Valipour et al. [63] developed a step-wise weight assessment ratio analysis (SWARA) based complex proportional assessment (COPRAS) framework to analyse Iranian construction project uncertainty. Khanzadi et al. [64] solved the dispute resolution problem in the construction sector by considering a grey number based discrete zero-sum two-person matrix game model. Keshavarz Ghorabaee et al. [65] presented the hybrid fuzzy step-wise weight assessment ratio analysis (SWARA) based 'evaluation based on distance from average solution' (EDAS) model for assessment of the construction equipment by taking sustainability into account.

3. Preliminaries

3.1. Dempster–Shafer (D–S) Evidence Theory

To deal with real world information, which may be ambiguous, various imprecise decision-making models based on probability theory, fuzzy set theory, and D–S evidence theory have been

developed [66]. D–S evidence theory directly expresses uncertain information by allocating the probability to the multiple object based subsets in lieu of individual items [67]. Due to its ability to compare pairs of evidence or belief functions when deriving new ones, and its superiority in an uncertain environment, evidence theory has been widely applied in various domains [22,34,39,68–70].

Certain basic definitions are now presented. Let U denote the frame of discernment representing a collective set of exhaustive and mutually exclusive events, and each element of 2^U (a power set in U) represents a proposition [22]. Based on these, basic probability assignment (BPA) is defined as follows:

Definition 1. *Basic Probability Assignment (BPA)*

A finite non-empty set of mutually exclusive and exhaustive hypotheses for any problem domain is called *its frame of discernment*. In lieu of a D–S evidence framework, the BPA is defined on a frame of discernment to express the imprecise judgements of experts [39]. Thus, if 2^U denotes the power set of a finite non-empty set U, then a BPA is defined as a mapping m satisfying (1) and (2):

$$m : 2^U \rightarrow [0, 1], \tag{1}$$

$$m(\phi) = 0 \; and \; \sum_{A \in 2^U} m(A) = 1, \tag{2}$$

where ϕ is an empty set and A is any element of 2^U. If $m(A) > 0$, A is called its focal element, and the union of all focal elements is the core of the mass function.

Example: Suppose there exists a task to assess a project. In the frame of D–S theory, the frame of discernment is the proposed project set $B = \{b_1, b_2, b_3\}$.

As per the expert view, a BPA can be created to express their assessment result: $m(\{b_1\}) = 0.2$; $m(\{b_2\}) = 0.7$; $m(\{b_2, b_3\}) = 0.1$, where $b_1 = [0, 40]$, $b_2 = [41, 70]$, $b_3 = [71, 100]$. In addition, the set $B = \{b_1, b_2, b_3\}$ is a frame of discernment in D–S theory with $m(\{b_1\}) + m(\{b_2\}) + m(\{b_2, b_3\}) = 1$.

3.2. D Numbers Theory

Although D–S evidence theory is operative in the data fusion problem, it is restricted to handling semantic information where linguistic variables are not mutually exclusive [39,70]. Intuitively, if some hypotheses of D–S theory are removed reasonably, the ability to represent and handle uncertain information may greatly improve. Overall, in many practical scenarios, the experts fail to have complete information, and the assessment is done solely on the basis of partial information, resulting in an incomplete BPA. Based on this idea, Deng [36] proposed D numbers theory, a generalisation of evidence theory, in order to characterise ambiguous data, as defined in (3) and (4) below:

Definition 2. *D Numbers [36]*

Let Ω be a finite nonempty set, D numbers is defined by a mapping:

$$D : \Omega \rightarrow [0, 1], \tag{3}$$

$$with \; \sum_{B \subseteq \Omega} D(B) \leq 1 \text{ and } D(\phi) = 0, \tag{4}$$

where ϕ is an empty set and B is a subset of Ω.

Compared with D–S evidence theory, the D numbers concept has the advantages that [34,39,42,71]:

- *Firstly*, D numbers with *nonexclusive hypothesis* in each element of the frame of discernment is more applicable for linguistic assessment.
- *Secondly*, in an evidence theory, a normal BPA must be *complete*, implying that the sum of all focal length elements in BPA is 1. D numbers allows the experts to input *incomplete and uncertain information* to the framework resulting in an incomplete BPA, thus releasing the completeness

constraint. Thus, if $\sum\limits_{B \subseteq \Omega} D(B) = 1$, the information is said to be complete, and for $\sum\limits_{B \subseteq \Omega} D(B) < 1$, the information is said to be incomplete.

Example 1. *Let an expert give his assessment on the condition of a bridge, using D numbers, in a scale interval of [0,100]. The expert express his assessment in an incomplete BPA framework as follows:*

$$D(\{a_1\}) = 0.5; \ D(\{a_2\}) = 0.3; \ D(\{a_1, \ a_2, \ a_3\}) = 0.1,$$

where $a_1 = [0, 60]$, $a_2 = [45, 75]$, and $a_3 = [65, 100]$.

Hence, the set of $\{a_1, a_2, a_3\}$ is not a frame of discernment, because the elements in the above set are not mutually exclusive. In addition, since $D(\{a_1\}) + D(\{a_2\}) + D(\{a_1, a_2, a_3\}) = 0.9 < 1$, the above information is incomplete. This example shows that the definition of D numbers is similar to the definition of the mass function.

Definition 3. *D numbers for a discrete set [36]*

For a discrete set $\Omega = \{b_1, b_2, \ldots, b_i, \ldots, b_n\}$, where $b_i \in R$ and $b_i \neq b_j (i \neq j)$, a special form of D numbers can be expressed as:

$$
\begin{cases}
D(\{b_i\}) = v_i \ (i = 1, 2, \ldots, n) \\
\text{or denoted as,} \\
D = \{(b_1, v_1), \ (b_2, v_2), \ldots, (b_i, v_i), \ldots, (b_n, v_n)\}, \\
\text{where } v_i > 0 \text{ and } \sum\limits_{i=1}^{n} v_i \leq 1.
\end{cases}
\tag{5}
$$

Definition 4. *Permutation invariability [22,71].*

Two D numbers $D_1 = \{(b_1, v_1), \ , \ldots, (b_i, v_i), \ldots, (b_n, v_n)\}$ & $D_2 = \{(b_n, v_n), \ , \ldots, (b_i, v_i), \ldots, (b_1, v_1)\}$ are said to be invariable if:

$$D_1 \Leftrightarrow D_2 \ . \tag{6}$$

Example 2. *If there are two D numbers:*

$D_1 = \{(0.0, \ 0.7), \ (1.0, \ 0.3)\}$ *and* $D_2 = \{(1.0, \ 0.3), (0.0, \ 0.7)\}$, *then,* $D_1 \Leftrightarrow D_2$.

Definition 5. *D numbers integration [6,36].*

Let $D = \{(b_1, v_1), \ (b_2, v_2), \ldots, (b_i, v_i), \ldots, (b_n, v_n)\}$ be a D number; then, the integration representation $I(D)$ of the D number is defined as:

$$I(D) = \sum_{i=1}^{n} b_i v_i \ \ . \tag{7}$$

Example 3. *Let $D = \{(1, \ 0.3), \ (2, \ 0.4), (3, \ 0.1), (4, 0.2), (5, 0.2)\}$, then $I(D) = 1 \times 0.3 + 2 \times 0.4 + 3 \times 0.1 + 4 \times 0.2 + 5 \times 0.2 = 3.2$.*

4. Methodology

4.1. D-CFPR: D Numbers Extended CFPR

Based on the additive transitive property, Herrera-Viedma et al. [30] put forward the consistent fuzzy preference relation (CFPR) for structuring an $n \times n$ decision matrix, which requires only $(n-1)$

pair wise comparisons, in lieu of $n(n-1)/2$ comparisons needed for constructing a fuzzy preference relation. Preserving both the reciprocity and transitivity properties, CFPR is constructed only on complete and certain information but fails to deal with cases containing insufficient information [34,36]. Citing the same deficiency as in the case of fuzzy preference relations, Deng et al. [39] proposed the concept of a D numbers preference relation encompassing the fuzzy preference relations of the D numbers domain. In addition, considering the insufficiency in traditional CFPRs, Zuo et al. [42] proposed a D numbers consistent fuzzy preference relation matrix, abbreviated as D-CFPR matrix using D numbers to express linguistic preferences given by experts to construct the CFPR. In the following steps, we will discuss the algorithmic methodology of D-CFPR, where distribution assessments are assessed under incomplete or missing information.

Step 1: Construct a D-CFPR matrix (R_D). The D numbers extended CFPR is advocated to reinforce the capability of CFPR to express uncertain and incomplete information. A D numbers based preference relation on a set of criteria $C = \{C_1, C_2, \ldots, C_n\}$ is characterized by a $n \times n$ matrix $R_D = \left[D_{ij} \right]_{n \times n}$ on the product set $C \times C$, whose elements are formulated as per Equation (8), and represented in matrix form (9):

$$R_D : C \times C \to D, \tag{8}$$

$$R_D = \begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_n \end{array} \begin{array}{cccc} C_1 & C_2 & \ldots & C_n \\ \left[\begin{array}{cccc} D_{11} & D_{12} & \cdots & D_{1n} \\ D_{21} & D_{22} & \cdots & D_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ D_{n1} & D_{n2} & \cdots & D_{nn} \end{array} \right] \end{array}, \tag{9}$$

where $D_{ij} = \left\{ \left(b^1_{ij}, v^1_{ij} \right), \left(b^2_{ij}, v^2_{ij} \right), \ldots, \left(b^p_{ij}, v^p_{ij} \right), \ldots \right\}$, $D_{ji} = \neg D_{ij} = \left\{ \left(1 - b^1_{ij}, v^1_{ij} \right), \left(1 - b^2_{ij}, v^2_{ij} \right), \ldots, \left(1 - b^p_{ij}, v^p_{ij} \right), \ldots \right\}$, $\forall i, j \in \{1, 2, \ldots, n\}$, $b^p_{ij} \in [0,1]$, $v^p_{ij} > 0$, $\sum_p v^p_{ij} = 1$. Obviously, $D_{ii} = \{(0.5, 1.0)\} \, \forall \, i \in \{1, 2, \ldots, n\}$ in R_D.

In Equation (9), is R_D called a D-CFPR as it is constructed based on $(n-1)$ pair wise comparisons, denoted as $\left\{ D_{12}, D_{23}, \ldots, D_{(n-1)n} \right\}$ representing a set of D numbers. Considering the set of preference values $B = \{D_{ji}, 1 \leq i < j \leq n\}$, the elements of which are denoted $D_{ji} = \left\{ \left(b^1_{ji}, v^1_{ji} \right), \left(b^2_{ji}, v^2_{ji} \right), \ldots, \left(b^k_{ji}, v^k_{ji} \right), \ldots \right\}$, which can also be represented as follows [42]:

$$D_{ji} = \frac{j-i+1}{2} - D_{i(i+1)} - D_{(i+1)(i+2)} - \ldots - D_{(j-1)j},$$

where each component $\left(b^k_{ji}, v^k_{ji} \right)$ in D_{ji} is obtained by:

$$\left. \begin{array}{l} b^k_{ji} = \frac{j-i+1}{2} - b^x_{i(i+1)} - b^y_{(i+1)(i+2)} - \ldots - b^k_{(j-1)j}, \quad \forall (x, y, \ldots, z) \\ v^k_{ji} = \sum\limits_{(x,y,\ldots z) \in \Omega} v^x_{i(i+1)} \times v^y_{(i+1)(i+2)} \times \ldots \times v^z_{(j-1)j}, \end{array} \right\}, \tag{10}$$

where $\Omega = \left\{ (x, y, \ldots, z) \,\middle|\, b^k_{ji} = \frac{j-i+1}{2} - b^x_{i(i+1)} - b^y_{(i+1)(i+2)} - \ldots - b^k_{(j-1)j} \right\}$, $\left(b^x_{i(i+1)}, v^x_{i(i+1)} \right)$ is the xth component of $D_{i(i+1)}$, $\left(b^y_{(i+1)(i+2)}, v^y_{(i+1)(i+2)} \right)$ is the yth component of $D_{(i+1)(i+2)}$, $\left(b^z_{(j-1)j}, v^z_{(j-1)j} \right)$ is the zth component of $D_{(j-1)j}$

Thus, based on the reciprocal property, the rest of the entries in D-CFPR (9) are calculated as per Equation (11) as follows:

$$D_{ji} = \neg D_{ij}, \quad \forall i, j \in \{1, 2, \ldots, n\}. \tag{11}$$

As per Equations (9)–(11), a D-CFPR can be constructed based on $(n-1)$ pair wise comparisons $\left\{ D_{12}, D_{23}, \ldots, D_{(n-1)n} \right\}$. In the D-CFPR generated above, some values of the $b'_{ij}s$ in D_{ij}, $i, j \in (1, 2, \ldots, n)$ that fall in the interval $[-a, 1+a]$, $a > 0$ need to be transformed using Equation (12):

$$f : [-a, 1+a] \rightarrow [0,1], \ f(r) = \frac{r+a}{1+2a}. \tag{12}$$

The transformation function (12) works as a normalisation, which transforms the values of $b'_{ij}s$ from $[-a, 1+a]$ to the interval [0,1].

Step 2: Determine the crisp matrix R_c. Convert the matrix $R_D = [D_{ij}]_{n \times n}$ in (9) to a *crisp matrix* $R_C = [c_{ij}]_{n \times n}$ (13) using the integration representation of D numbers (as per Equation (7)), where each element $c_{ij} = I(D_{ij}) \ i, j = 1, 2, \ldots, n$:

$$R_c = [c_{ij}]_{n \times n} = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & c_{22} & \cdots & c_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n1} & c_{n2} & \cdots & c_{nn} \end{bmatrix}. \tag{13}$$

Step 3: Construct a probability matrix R_p. Based on the crisp matrix R_C (13), construct a probability matrix $R_p = [p_{ij}]_{n \times n}$ (14), representing the preference probability between a pair wise set of n criteria $C = \{C_1, C_2, \ldots, C_n\}$:

$$R_p = [p_{ij}]_{n \times n} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix}. \tag{14}$$

In R_p, the element $p_{ij} = \Pr(C_i \succ C_j), \forall i, j \in \{1, 2, \ldots \ldots, n\}$, where "$\succ$" represents *"prefer to"*. Based on (13), a set of rules is suggested to generate R_p.

- For the elements satisfying $c_{ij} + c_{ji} = 1.0$,

  ○   If $c_{ij} > 0.5$, then $\Pr(C_i \succ C_j) = 1$ and $\Pr(C_i \prec C_j) = 0$,
  ○   If $c_{ij} \leq 0.5$, then $\Pr(C_j > C_i) = 1$ and $\Pr(C_i > C_j) = 0$.

- When $c_{ij} + c_{ji} > 1.0 : c_{ij} \geq 0.5 \ and \ c_{ji} \geq 0.5$,

  ○   If $c_{ij} \geq 0.5$, then $\Pr(C_i \succ C_j) = 1$ and $\Pr(C_j \succ C_i) = 0$,
  ○   If $c_{ji} \geq 0.5$, then $\Pr(C_j \succ C_i) = 1$ and $\Pr(C_i \succ C_j) = 0$.

- when $c_{ij} + c_{ji} < 1.0 : c_{ij} < 0.5 \ and \ c_{ji} < 0.5$.

In this condition, the unallocated preference *(up)* is $c_{up} = 1 - (c_{ij} + c_{ji})$. The probability of one criteria outperforming another criteria is as follows:

  ○   If $c_{ij} < 0.5$, then $\Pr(C_i \succ C_j) = 1 - \frac{(0.5 - c_{ij})}{c_{up}}$,
  ○   If $c_{ji} < 0.5$, then $\Pr(C_j \succ C_i) = 1 - \frac{(0.5 - c_{ji})}{c_{up}}$.

Step 4: Construct a triangular probability matrix R_p^T. Rank the criteria using the triangularisation procedure, viz. by maximising the sum of the values above, the main diagonal in the $n \times n$ square matrix in the final order is given as:

- First, sum up each row of the $n \times n$ matrix and determine the row number with maximum value.
- Then, assuming the obtained row number is k, delete the k-th row and k-th column in the matrix.
- Replicate the two procedures above until the matrix is empty.

Thus, by applying this defined row deletion order operation on the matrix $R_p = [p_{ij}]_{n \times n}$ (14), construct the triangular probability matrix R_p^T, shown in (15):

$$R_p^T = \left[p_{ij}^T \right]_{n \times n} = \begin{bmatrix} p_{11}^T & p_{12}^T & \cdots & p_{1n}^T \\ p_{21}^T & p_{22}^T & \cdots & p_{2n}^T \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1}^T & p_{n2}^T & \cdots & p_{nn}^T \end{bmatrix}. \tag{15}$$

Step 5: Construct triangulated crisp matrix R_c^T. Firstly, the crisp matrix R_c (13) is triangulated based on the triangular matrix R_p^T (15). From that step, the triangulated crisp matrix R_c^T (16) is derived:

$$R_c^T = \left[c_{ij}^T \right]_{n \times n} = \begin{bmatrix} c_{11}^T & c_{12}^T & \cdots & c_{1n}^T \\ c_{21}^T & c_{22}^T & \cdots & c_{2n}^T \\ \vdots & \vdots & \ddots & \vdots \\ c_{n1}^T & c_{n2}^T & \cdots & c_{nn}^T \end{bmatrix}. \tag{16}$$

Secondly, for elements satisfying $R_c^T(i, j) + R_c^T(j, i) < 1$, a new "*polishing operation*" (17) is implemented to obtain a triangulated crisp matrix R_k^T (18):

$$R_k^T(i, j) = R_c^T(i, j) + \frac{1 - \left[R_c^T(i, j) + R_c^T(j, i) \right]}{2}, \tag{17}$$

$$R_k^T = \left[k_{ij}^T \right]_{n \times n} = \begin{bmatrix} k_{11}^T & k_{12}^T & \cdots & k_{1n}^T \\ k_{21}^T & k_{22}^T & \cdots & k_{2n}^T \\ \vdots & \vdots & \ddots & \vdots \\ k_{n1}^T & k_{n2}^T & \cdots & k_{nn}^T \end{bmatrix}. \tag{18}$$

Step 6: *Calculate the relative priority weights of the criteria.* Assume that the weight vector is $W = (w_i)^T$, where $w_i(i = 1, 2, \ldots, n)$ are the weights of criteria $C_i(i = 1, 2, \ldots, n)$. The elements above and alongside the main diagonal of the matrix $R_k^T = \left[k_{ij}^T \right]_{n \times n}$ (18) indicate the weight relationship of the criteria. Thus, by adding some necessary constraints, a set of Equation (19) is formed:

$$\begin{cases} \lambda(w_2 - w_1) = k_{22}^T - k_{12}^T \\ \lambda(w_3 - w_2) = k_{33}^T - k_{23}^T \\ \ldots \ldots \ldots \\ \lambda(w_n - w_{n-1}) = k_{nn}^T - k_{(n-1)n}^T \end{cases}, \tag{19}$$

where λ indicates the *granular information* about the pairwise comparison, which reveals the expert's perceptive competency. The value of each weight $w_i(i = 1, 2, \ldots, n)$, subjected to the parameter λ, relates to the expert's cognitive aptitude. The values of λ highly depend on the influence of the experts' judgment and belief function. Thus, a feasible outline (20) is obtained as follows:

$$\lambda = \begin{cases} \lceil \underline{\lambda} \rceil, & \text{The information has high credibility} \\ n, & \text{The information has medium credibility} \\ \frac{n^2}{2}, & \text{The information has low credibility} \end{cases}, \tag{20}$$

where $\underline{\lambda}$ signifies the lower bound of λ, $\lceil \underline{\lambda} \rceil = \min\{k \in \mathbb{Z} | k \geq \underline{\lambda}\}$, and n is the number of alternatives [39]. The concrete priority weight value of each criteria is calculated here when $\lambda = n$.

Step 7: Inconsistency for the D-CFPR. The traditional CFPR is fully consistent when constructed under the transitivity property for $n - 1$ preference values. The D numbers based CFPR is *consistent*, but, when reduced to classical CFPR, it shows inconsistency under *uncertain or incomplete* information. Thus, to express this inconsistency of D-CFPRs, an inconsistency degree (ID) (21) is defined, based on the triangular probability matrix R_p^T (18), as follows:

$$I.D. = \frac{\sum\limits_{i=1,j<i}^{n} R_p^T(i,j)}{n(n-1)/2}, \tag{21}$$

where $R_p^T(i,j)$ is an element of R_p^T, and n is the number of comparison objects. This emphasises that the inconsistency of the D matrix, and its acceptable level is decided by the DMs, whose subjective requirement regulates the tolerance level of the aforementioned inconsistency.

4.2. Evaluating the Risk Criteria Weight Using D-ANP

The evaluation of D-ANP methodology is composed of two phases.

The first phase emphasises the formation of pairwise judgments for every dependent relationship among given criteria $C_i(i = 1, 2, \ldots, n)$, and determination of their priority weight. The priority weights thus obtained are input to the system-with-feedback supermatrix for computing the network influences amongst the different relationships.

The second phase, namely supermatrix evaluation, incorporates five steps: formation of the unweighted supermatrix, formation of the weighted supermatrix, normalisation of the weighted supermatrix (a column stochastic matrix), and finally convergence to a solution using the limited supermatrix.

The converged supermatrix will provide us with the relative priorities for each of the criteria (*or sub-criteria*) considered within clusters of the decision framework. Thus, the following algorithmic steps of D-ANP are as follows:

Step 1: Model construction and problem structuring. First, we properly outline the decision problem with detailed criteria and sub-criteria (*if taken*) and then delimit the cluster's (*dimension's*) network and elements (*criteria set*) within the given clusters. Next, we decide which inter- and inner-dependencies will prevail in the decision problem and clusters of the over-all feedback system.

Step 2: Pairwise comparison matrices and priority vectors. The expert inputs prerequisite for the ANP method are the pairwise judgments of the elements within each cluster, from which inter-and-inner-dependence matrices are formed. Primarily, three categories of pairwise comparisons are formed. First, the inner dependence comparison matrix, based on the criteria of different clusters (dimensions), is used to get the priority weight vector. Then, the pairwise comparison matrices obtained from criteria with respect to other factors (criteria) of the same cluster (dimension). Finally, the pairwise comparison matrix is developed by considering the factor (criteria) of a cluster (dimension) among factors (criteria) of the other cluster (dimension), which affect the criteria.

These pairwise comparison matrices, along with their valuation elicitation, constitute a modified version of D-AHP [22] and D-CFPR [34]. Based on Section 4.1, a brief summary for getting the priority weight of any pairwise comparison matrix is given below, the graphical description of which is shown in Figure 1.

- In the first step, the D-CFPR matrix $R_D = \left[D_{ij}\right]_{n \times n}$, is constructed for n criteria, by considering the system as an input using Equations (9)–(12).
- The D-CFPR matrix formed (R_D), is converted to a crisp matrix $R_C = \left[c_{ij}\right]_{n \times n}$, using the integration representation of D number, shown in Equation (13).
- The probability matrix $R_p = \left[p_{ij}\right]_{n \times n}$ is then constructed based on the derived crisp matrix (R_c) using Equation (14), and it satisfies a set of rules in Step 3 of Section 4.1.
- In the next step, using Equation (15), triangularisation $R_p^T = \left[p_{ij}^T\right]_{n \times n}$ is applied to the probability matrix using local information that contains the preference relations of pairwise criteria.
- Lastly, applying Equations (16)–(19), the crisp based triangular matrix $R_c^T = \left[c_{ij}^T\right]_{n \times n}$, is obtained, and relative priority weights $w_i(i = 1, 2, \ldots, n)$ of each criteria $C_i(i = 1, 2, \ldots, n)$, based on clusters *(dimensions)* are calculated, thereby checking its inconsistency as per Equation (21).
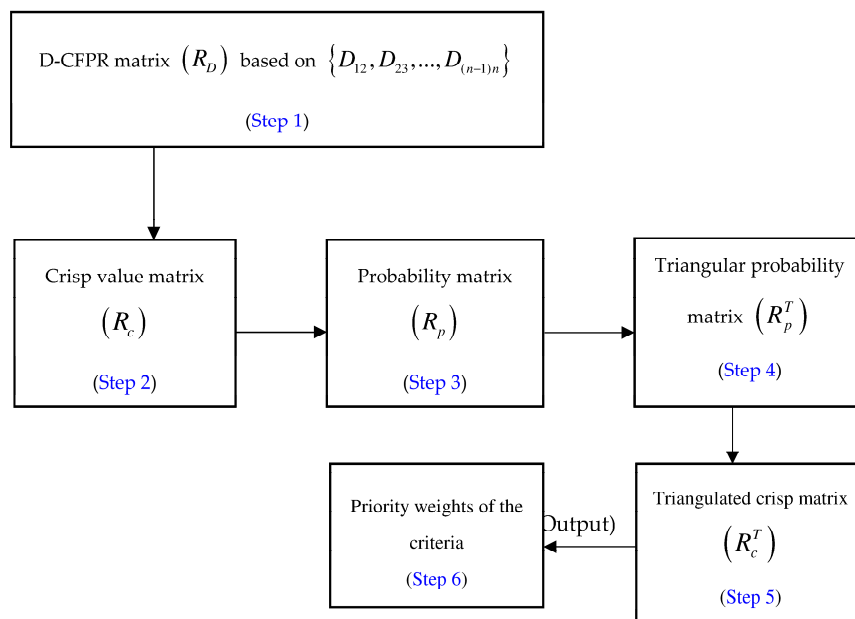
Figure 1. Procedure to obtain priority weights of criteria based on D numbers extended consistent fuzzy preference relation.

Step 3: Formation of the unweighted supermatrix. The local priority weights resulting from the pairwise comparison are used as input in suitable columns of the unweighted constructed supermatrix, to obtain the global priorities in a system. As a result, a supermatrix takes the form of a partitioned matrix, each segment of which represents an association between two clusters in the given system. Thus, the supermatrix W Equation (22) formed is represented by sub-matrices W^{ij} as $W = \left[W^{ij} \right]_{n \times n} (i, j = 1, 2, \ldots, n)$. The size of the sub-matrix W^{ij} Equation (23) depends on the compared factors (criteria). Interdependency between clusters is illustrated in Equation (22) by analysing both inter- and intra-relations among clusters.

Arrange all priority vectors, representing the impact of a given set of elements in a cluster on another element in the network, as sub-columns of the corresponding column of an unweighted supermatrix W as in Equations (22) and (23). This is composed of k clusters $\{D_1, D_2, \ldots, D_k\}$, and linkages of these clusters $\{e_{k1}, e_{k2}, \ldots, e_{kn_k}\}$, are elements of the cluster $D_p (p = 1, 2, \ldots, k)$. Each column of the sub-matrix W^{ij} Equation (23) is the priority vector acquired from the identical pairwise judgment, indicating the significance of the elements in the ith cluster with respect to an element in the jth cluster:

$$
W = \begin{array}{c} \\ \\ D_1 \\ \\ \\ \\ \\ D_2 \\ \\ \\ \\ \\ \\ D_k \\ \\ \end{array}
\begin{array}{c}
e_{11} \\ e_{12} \\ \vdots \\ e_{1(n_1)} \\ e_{21} \\ e_{22} \\ \vdots \\ e_{2(n_2)} \\ e_{k1} \\ e_{k2} \\ \vdots \\ e_{k(n_k)}
\end{array}
\begin{array}{c}
\overset{\displaystyle D_1}{\overbrace{e_{11} e_{12} \ldots e_{1(n_1)}}} \quad \overset{\displaystyle D_2}{\overbrace{e_{21} e_{22} \ldots e_{2(n_2)}}} \quad \cdots \quad \overset{\displaystyle D_k}{\overbrace{e_{k1} e_{k2} \ldots e_{k(n_k)}}} \\
\left[\begin{array}{cccc}
W^{11} & W^{12} & \cdots & W^{1k} \\
\\
W^{21} & W^{22} & \cdots & W^{2k} \\
\\
\cdot & \cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot & \cdot \\
\\
W^{k1} & W^{k2} & \cdots & W^{kk}
\end{array} \right]
\end{array}
\quad where \ \sum_{j=1}^{k} (n_j) = n, \quad (22)
$$

$$W^{ij} = \begin{bmatrix} W_{11}^{ij} & \cdots & W_{1j}^{ij} & \cdots & W_{1n_j}^{ij} \\ \vdots & & \vdots & \cdots & \vdots \\ W_{i1}^{ij} & \cdots & W_{ij}^{ij} & \cdots & W_{in_j}^{ij} \\ \vdots & & \vdots & & \vdots \\ W_{n_i1}^{ij} & \cdots & W_{n_ij}^{ij} & \cdots & W_{n_in_j}^{ij} \end{bmatrix} \quad i,j = 1,2,\ldots,k,. \tag{23}$$

Step 4: Determine the normalised weighted supermatrix. If there is no linkage between clusters D_k and D_l, then the sub-matrix W^{kl} equals zero. We compute the weighted supermatrix $W^a = \left[\widetilde{W}^{ij}\right]_{n\times n}$, by multiplying the unweighted matrix $W = \left[W^{ij}\right]_{n\times n}$, Equation (23) by priority of dimensions $V_j (j = 1,2,\ldots,n)$, in this stage. As the weighted supermatrix (W^a) needs to be stochastic, we normalise each column of it, and develop meaningful limiting priorities for determining overall cluster influences. This normalisation procedure ensures that the weighted supermatrix is column stochastic; it is finally represented by matrix $\hat{W} = \left[\overline{W}^{ij}\right]_{n\times n}$.

Step 5: Compute the limiting priorities for criteria weights. Finally, the column stochastic weighted supermatrix is raised to an appropriately large power until it converges. Thus, the weighted supermatrix $\hat{W}$ is raised to limiting powers $(\hat{W})^{2m+1}$, m being an arbitrarily large number, to attain a steady-state limiting matrix W^q. Details are shown in Equation (24):

$$W^q = \lim_{k\to\infty} (\hat{W})^{2m+1}. \tag{24}$$

The priority weight of criteria for the corresponding clusters (dimensions) can now be found in the rows of the limiting supermatrix W^q. The limiting supermatrix provides the priority information for the elements of each individual cluster. The strategy outcome with the highest value should be selected from the cluster of criteria. Other priority rankings in different clusters are also provided.

4.3. D-MABAC for Ranking Alternatives

The MABAC methodology was developed by Pamucar and Cirovic [44] to handle problems in MCDM. D numbers is a new representation of uncertain information that can denote the more imprecise based conditions. Thus, the combination of MABAC and D numbers is a new experiment to make decisions in an uncertain environment. The basic setting of the MABAC technique is revealed in the definition of the distance of the criterion function of each of the observed alternatives from the approximate border area [72]. The algorithmic steps displays the execution process for the aforesaid D-MABAC methodology in six steps as follows:

Step 1: Constructing the initial decision matrix M. Initially, the assessment of m alternatives in respect of n criteria is carried out. The alternatives are represented in vector form $A_i = (d_{i1}, d_{i2}, \ldots, d_{in})$, where $d_{ij}(j = 1,2,\ldots,n)$ denotes the value (*in D numbers format*) for the i alternative ($i = 1,2,\ldots,m$) according to j criteria for matrix $M = \left[d_{ij}\right]_{m\times n}$. Details shown in decision-matrix (25):

$$M = \begin{bmatrix} d_1(\{1\}) = d_{11} & d_1(\{2\}) = d_{12} & \cdots & d_1(\{n\}) = d_{1n} \\ d_2(\{1\}) = d_{11} & d_2(\{2\}) = d_{22} & \cdots & d_2(\{n\}) = d_{2n} \\ \cdots & \cdots & \ddots & \cdots \\ d_m(\{1\}) = d_{m1} & d_m(\{2\}) = d_{m2} & \cdots & d_m(\{n\}) = d_{mn} \end{bmatrix}. \tag{25}$$

Next, applying Equation (8), (i.e., integration representation of D numbers) on the elements d_{ij} ($i = 1,2,\ldots,m; j = 1,2,\ldots,n$) of decision matrix $M = \left[d_{ij}\right]_{m\times n}$, crisp decision matrix $X = \left[I(d_{ij})\right]_{m\times n}$ is formed as per Equation (26) as follows:

$$
X = \begin{bmatrix}
I(d_{11}) & I(d_{12}) & \cdots & I(d_{1n}) \\
I(d_{21}) & I(d_{22}) & \cdots & I(d_{2n}) \\
\cdots & \cdots & \ddots & \cdots \\
I(d_{m1}) & I(d_{m2}) & \cdots & I(d_{mn})
\end{bmatrix}_{m \times n}
= \begin{bmatrix}
x_{11} & x_{12} & \cdots & x_{1n} \\
x_{21} & x_{22} & \cdots & x_{2n} \\
\cdots & \cdots & \ddots & \cdots \\
x_{m1} & x_{m2} & \cdots & x_{mn}
\end{bmatrix}_{m \times n}
\quad \text{where each } x_{ij} = I(d_{ij}). \quad (26)
$$

Step 2. Normalisation of the elements of the initial matrix X. The elements of the normalized matrix $N = [t_{ij}]_{m \times n}$ are obtained using the following expressions:

$$
N = \begin{bmatrix}
t_{11} & t_{12} & \cdots & t_{1n} \\
t_{21} & t_{22} & \cdots & t_{2n} \\
\cdots & \cdots & \ddots & \cdots \\
t_{m1} & t_{m2} & \cdots & t_{mn}
\end{bmatrix}, \quad (27)
$$

where

$$
t_{ij} = \begin{cases}
\dfrac{x_{ij} - x_i^-}{x_i^+ - x_i^-}, & \text{for "benefit type" criteria elements} \\[2mm]
\dfrac{x_{ij} - x_i^+}{x_i^- - x_i^+}, & \text{for "cost type" criteria elements}
\end{cases}, \quad (28)
$$

where $x_{ij} = I(d_{ij})$ and the components $x_i^+ = \max(x_1, x_2, \ldots, x_m)$, $x_i^- = \min(x_1, x_2, \ldots, x_m)$ of the decision matrix (X) represent the maximum and minimum values of the criteria $C_j(j = 1, 2, \ldots, n)$, by alternatives $A_i(i = 1, 2, \ldots, m)$.

Step 3. Calculation of the elements of weighted matrix (V). The elements of the weighted matrix $V = [v_{ij}]_{m \times n}$, are calculated using the following equations:

$$
V = \begin{bmatrix}
v_{11} & v_{12} & \cdots & v_{1n} \\
v_{21} & v_{22} & \cdots & v_{2n} \\
\cdots & \cdots & \ddots & \cdots \\
v_{m1} & v_{m2} & \cdots & v_{mn}
\end{bmatrix}, \quad (29)
$$

$$
v_{ij} = w_j \cdot (t_{ij} + 1), \quad (30)
$$

where t_{ij} are the elements of the normalised matrix $N = [t_{ij}]_{m \times n}$ and $w_i(j = 1, 2, \ldots, n)$ the weight coefficients of criteria, respectively.

Step 4. Determine the border approximation area matrix (G). The elements of the border approximation area (BAA) for each criterion $C_j(j = 1, 2, \ldots, n)$ are determined as follows:

$$
g_j = \left(\prod_{i=1}^{m} v_{ij} \right)^{1/m}, \quad (31)
$$

where v_{ij} are the elements of the weighted matrix $V = [v_{ij}]_{m \times n}$, and m is the total number of alternatives. After calculating the value $g_j(j = 1, 2, \ldots, n)$, for each criterion, the BAA matrix (G) is formed with format $n \times 1$ (n = the total number of criteria, according to which the selection is made from the alternatives).

$$
G = [g_1 \ g_2 \ \cdots \ g_n]_{1 \times n}. \quad (32)
$$

Step 5. Calculation of the distance of the alternative from the BAA for the matrix elements (Q). The distance (q_{ij}) of the alternatives $A_i(i = 1, 2, \ldots, m)$ from the BAA matrix $G = [g_1 \ g_2 \ \cdots \ g_n]$ is determined as the difference between the elements $v_{ij}(i = 1, 2, \ldots, m; j = 1, 2, \ldots, n)$ in the weighted matrix $V = [v_{ij}]_{m \times n}$, and the value $g_j(j = 1, 2, \ldots, n)$ of the BAA (G). The distance $q_{ij}(i = 1, 2, \ldots, m; j = 1, 2, \ldots, n)$ are elements of a matrix $Q = [q_{ij}]_{m \times n}$ and are shown in Equation (33):

$$Q = \begin{bmatrix} v_{11} - g_1 & v_{12} - g_2 & \cdots & v_{1n} - g_n \\ v_{21} - g_1 & v_{22} - g_2 & \cdots & v_{2n} - g_n \\ \cdots & \cdots & \ddots & \cdots \\ v_{m1} - g_1 & v_{m2} - g_2 & \cdots & v_{mn} - g_n \end{bmatrix} = \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1n} \\ q_{21} & q_{22} & \cdots & q_{2n} \\ \cdots & \cdots & \ddots & \cdots \\ q_{m1} & q_{m2} & \cdots & q_{mn} \end{bmatrix}. \tag{33}$$

Alternative $A_i (i = 1, 2, \ldots, m)$ can belong to BAA (G), upper approximation area (G^+), or lower approximation area (G^-), i.e., $A_i \in \{G \vee G^+ \vee G^-\}$ and are determined as per Equation (34):

$$A_i \in \begin{cases} G^+ \ if \ q_{ij} > 0 \\ G \ \ if \ q_{ij} = 0 \\ G^- \ if \ q_{ij} < 0 \end{cases}, \ where \ each \ q_{ij} = v_{ij} - q_j. \tag{34}$$

Step 6. Ranking of the alternatives. A calculation of the values of the criterion functions for the alternatives is obtained as the sum of the distance of the alternatives from the BAA (q_{ij}). Using Equation (35), we calculate the sum of the elements q_{ij} of matrix (Q) by rows, and obtain the final values of the criterion functions $\hat{S}_i$ $(i = 1, 2, \ldots, m)$, for the alternatives $A_i (i = 1, 2, \ldots, m)$:

$$\hat{S}_i = \sum_{j=1}^{n} q_{ij}, \ i = 1, 2, \ldots, m; \ j = 1, 2, \ldots, n. \tag{35}$$

5. Numerical Example: Risk Assessment in a Construction Project

5.1. Identification of Construction Projects Risk Indicators and Their Mitigation Strategies

For categorising and managing construction project risks effectually, several methodologies are recommended in the literature [43,73–75]. Keeping this in mind, we proposed the hybrid D-ANP-MABAC approach for the risk assessment of projects in the construction sector involving uncertain and incomplete information data. The authors employed a combination of questionnaire surveys involving literature reviews and subjective judgments of highly proficient experts to detect different risk response strategies that optimise the performance of construction projects. The proposed methodology incorporates the knowledge and experience of ten experts (five *technical* and five *management* based experts) for risk identification and structuring, along with proper risk mitigation strategies. The demographic profile of the respondents is given in Table 1.

Table 1. Summary of demographic profile of respondents.

	Characteristics	Frequency	Percentage (%)
Age group	21–31	2	20
	31–39	4	40
	39–45	3	30
	45–58	1	10
Gender	Female	4	40
	Male	6	60
Level of Education	Bachelor's degree	4	40
	Master's degree	5	50
	Higher	1	10
Role of respondents	Chief personal officer	1	10
	Manager or general manager	2	20
	Staff or assistant manager	1	10
	Project risks analyst	2	20
	Purchasing manager	1	10
	Construction site engineer	3	30
Years of experience in construction sector	Above 15 years	2	20
	10 years~15 years	4	40
	5 years~10 years	3	30
	Less than 5 years	1	10
	Total available number	10	

Based on the literature review of papers discussed in Table 2, the DMs consider *nine construction project risk criteria* identified under *three dimensions*: political instability (C_1), economic risk (C_2), and social risk (C_3). These are defined as environmental based *external risks* (D_1). Technological risk (C_4), work quality risk (C_5), and time and cost risk (C_6) are defined as construction process based *project risks* (D_2). Resource risk (C_7), documents and information risk (C_8), and stakeholder's risk (C_9) are defined under intrinsic criteria based *internal risks* (D_3). Details are given below in Table 3.

Table 2. Risk factors involved in construction projects.

Risk Indicators in Project Based Construction Management	References
Environmental risk; political, social and economic risk; contractual agreement risk; financial risk; construction risk; project design risk; market risk.	[1]
Safety risk, quality risk, environmental risk, political risk, project site risk, project complexity risk.	[53]
Quality risks, personnel risks, cost risks, deadline risks, strategic decision risks, external risks.	[17]
Operational risk, economic risk, political risk, financial risk, legal risk, currency and inflation risk, corruption risk, tendering procedures.	[3]
Political risks, economic risk, social risk, weather risk, cost, quality risk, technical risk, construction risk, resources risk, project member risk, information risk, construction site risks.	[23]
Resources risk, inexperience of project members, lack of motivational approach, design errors risk, efficiency risk, technical risk, quality risk.	[21]
Inflation risk, Payment security risk, Programme overrun risk, subcontractor pricing risk.	[56]
Political risk, economic risk, natural risk, legal risk, contractor risk, financial risk, management risk, equipment risk, designer risk.	[25]
Management risk, project risk, design risk, financial risk, operational risk, external risk.	[14]
Information risk, cost risks, lack of coordination, project schedule risk, lack of professional planning, legal dispute risk.	[15]
Designing risk, time risk, budget risk, labour risk, political risk.	[16]
Design risk, payment delay risk, funding risk, quality risk, labour dispute risks, natural disaster risk, exchange rate fluctuation risk, political instability, site condition risks, insurance inadequacy risk.	[9]
Technical risks, organisational risks, socio-political risks, environmental risks, financial risks.	[6]
Inflation (economic) risk, environmental and geological risk, design risk, construction delay risk, inadequate managerial skills risk, resource risk.	[29]

Table 3. Dimensions and risk criteria involved in construction projects.

Risk Dimension	Risk Criteria *	Brief Descriptions of Causes of the Mentioned Criteria Risks
External risks (D_1)	Political instability (C_1)	Frequent changes in government due to disputes among political parties, change in law due to local government's unpredictable new regulations, needless influence by local government on court proceedings regarding project disputes.
	Economic risk (C_2)	Fluctuation in currency exchange rate, unpredictable inflation due to immature banking systems, payment delays due to poor funding for project, inadequate forecasting about market demand.
	Social risk (C_3)	Racial tension and differences in work culture and language between foreign and local partners.
Project risk (D_2)	Technological risk (C_4)	Risk of insufficient technology, improper design, unexpected design changes; inadequate site investigation; change in construction procedures and insufficient resource availability.
	Work quality risk (C_5)	Corruption, including bribery, at sites; obsolete technology and practices by the local partner; low local workforce labor productivity due to poor skills or inadequate supervision; improper quality control; local partner tolerance of defects and inferior quality.
	Time and cost risk (C_6)	Delays due to disputes with contractors, natural disasters, and lack of availability of utilities; risk of labor disputes and strikes; insufficient cash flow, improper measurements, ill planned schedules, and delays in payment; lack of proper benchmarking and monitoring of construction activities.
Internal risks (D_3)	Resource risk (C_7)	Difficulty in hiring suitable skilled employees; risk of defective material from suppliers; risk of labor, materials, and equipment availability; poor competence and productivity of labor *.
	Documents and information risk (C_8)	Intellectual property protection risk from former local employees, partners, and third parties; corporate fraud including unexpected increases in turnover, unexpected resignations of financial advisers, intentional or unintentional negligence by auditors, bankers, or creditors.
	Stakeholder's risk (C_9)	Local partner's creditworthiness: Information on local partner's accounts lucidity, financial soundness, foreign exchange liquidity, staff reliability. Termination of joint ventures (JV): unfair dividends, e.g., assets, shares, and benefits, to foreign firms by local partner upon termination of JV contract.

* Sources: [4,6,9,23,27,52,75].

In past decades, construction businesses were constrained to use only a limited number of risk management procedures, even though they were not suitable for all situations. For example, Lyons

and Skitmore [50] found that brainstorming is the most common risk identification technique used in the Queensland engineering construction industry. Forbes et al. [74] developed a matrix for selecting appropriate risk management techniques such as artificial intelligence, probabilistic analysis, sensitivity analysis, and decision trees in the built environment for each stage of risk management. In this paper, based on the brainstorming method, the experts sought five alternative construction project risk response mitigation strategies, as detailed in Table 4.

Table 4. Construction risks response strategies.

Alternative (s)	Preventive Management Techniques	References
A_1	Proper scheduling for getting updated project information.	[9]
A_2	Adjust plans for scope of work and estimates to counter risk implications.	[2]
A_3	Get information about local partner's credibility from present and past business partners.	[4]
A_4	Transfer or share risks to/with other parties.	[6]
A_5	Merger and diversification of projects.	[23]

5.2. Calculating Risk Based Criteria Weight Using D-ANP Framework

In this section, the weights of the risk based criteria in construction projects are calculated by D-ANP. The ANP has substantial influence in MCDM problems involving a wide range of factors and sub-factors. In the ANP, a decision problem is transformed into a network structure that allows both inter-intra dependency and feedback among the decision clusters, and even amongst elements within the same clusters. In this phase, the decision group is asked to make pairwise comparison matrices for priority weights of three dimensions and nine criteria (as detailed in Table 3).

Using Steps 1–6 (of Section 4.1) of D-CFPR, the priority weights are calculated in the decision matrices. The algorithmic steps of D-ANP are shown below:

Step 1: Construction of the hierarchy of criteria and alternative risks strategies. The clearly defined risk based construction project model is decomposed into a logical system like a network. Based on the hierarchy of Figure 2, we have five risk mitigation strategies $A_i (i = 1, 2, \ldots, 5)$ in Level 4 hierarchical position, three dimensions $D_j (j = 1, 2, 3)$ (external, project, and internal risk) in Level 2, and corresponding to each dimension, a total of nine criteria $C_j (j = 1, 2, \ldots, 9)$ in Level 3.

Step 2: Determination of the pairwise comparison matrices and priority vectors within clusters. The D numbers based preference matrix is first constructed before calculating the weight of the indicators using the ANP supermatrix. Here, we present the process of determining the priority weight of criteria (C_1, C_2, and C_3) for risk dimension *external risk* with respect to the criterion C_6 under dimension *Project risk*.

First, we calculate the relative significance of sub-criteria (C_1, C_2, and C_3) relative to sub-criterion C_6, to construct the inner dependence matrix built on the D numbers based preference relation $R_D = [D_{ij}]_{3 \times 3}$. In this case, the preference modelled by a set of D numbers (*based on DM's choice*) involving both *uncertain entry* (i.e., $D_{12} = \{(0.55, 0.7), (0.65, 0.3)\}$ and *incomplete entry* $D_{23} = \{(0.75, 0.8)\}$, respectively:

$$R_D = \begin{bmatrix} D_{11} & D_{12} & D_{13} \\ D_{21} & D_{22} & D_{23} \\ D_{31} & D_{32} & D_{33} \end{bmatrix} = \begin{bmatrix} \{(0.5, 1.0)\} & \{(0.55, 0.7), (0.65, 0.3)\} & - \\ - & \{(0.5, 1.0)\} & \{(0.75, 0.8)\} \\ - & - & \{(0.5, 1.0)\} \end{bmatrix}.$$

The standard CFPR cannot handle this case, but D-CFPR (Equations (9)–(12) in Section 3.1) is effective to fill up the rest of the matrix elements in $R_D = [D_{ij}]_{3 \times 3}$ as follows:

$$R_D = \begin{bmatrix} \{(0.5, 1.0)\} & \{(0.55, 0.7), (0.65, 0.3)\} & \{(0.80, 0.56), (0.9, 0.24)\} \\ \{(0.45, 0.7), (0.35, 0.3)\} & \{(0.5, 1.0)\} & \{(0.75, 0.8)\} \\ \{(0.2, 0.56), (0.1, 0.24)\} & \{(0.25, 0.8)\} & \{(0.5, 1.0)\} \end{bmatrix}.$$

Then, the D numbers based CFPR matrix $R_D = [D_{ij}]_{3\times3}$ is converted to a crisp mode, $R_C = [c_{ij}]_{3\times3}$, using Equation (13), and the integration representation of D numbers Equation (7), shown below:

$$R_c = I(R_D) = \begin{bmatrix} 0.5 & 0.58 & 0.66 \\ 0.42 & 0.5 & 0.60 \\ 0.13 & 0.20 & 0.5 \end{bmatrix}.$$

Applying the preference rules proposed for D-CFPR (in Step 3 of Section 4.1) and using Equation (14), the probability matrix $R_p = [p_{ij}]_{3\times3}$ is constructed:

$$R_p = \begin{bmatrix} 0 & 1 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}.$$

Following the process (as mentioned in Step 4 of Section 4.1) of the D-CFPR methodology, we obtain the triangulated matrix $R_p^T = [p_{ij}^T]_{3\times3}$. Using the triangularisation method, the ranking of the indicators is calculated and shown as: $I_1 \succ I_2 \succ I_3$, where the symbol "$\succ$" indicates preference,

$$R_p^T = \begin{bmatrix} 0 & 1 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}.$$

We next evaluate the relative weights of the risk criteria. *First*, based on the ranking of the risk criteria in the triangulated matrix R_p^T, the crisp matrix R_c, is converted to a triangular crisp matrix R_c^T, as per Equation (16):

$$R_c^T = \begin{bmatrix} 0.5 & 0.58 & 0.66 \\ 0.42 & 0.5 & 0.60 \\ 0.13 & 0.20 & 0.5 \end{bmatrix}.$$

Next, for elements satisfying $R_c^T(i, j) + R_c^T(j, i) < 1$, a new polishing operation Equation (17) is executed and, by also applying Equation (18), a novel triangulated crisp matrix $R_k^T = [k_{ij}^T]_{3\times3}$ is obtained:

$$R_k^T = \begin{bmatrix} 0.5 & 0.58 & 0.76 \\ 0.42 & 0.5 & 0.70 \\ 0.21 & 0.24 & 0.5 \end{bmatrix}.$$

Finally, applying Equation (19), a group of equations is built to calculate the priority weight $w_i(i = 1, 2, \ldots, n)$ of each risk-based criterion. Applying the weight relation of the indicators in matrix mode, and incorporating necessary constraints, the weight equations are constructed and shown below:

$$\begin{cases} \lambda(w_1 - w_2) = 0.58 - 0.5 \\ \lambda(w_2 - w_3) = 0.76 - 0.5 \\ w_1 + w_2 + w_3 = 1 \\ \lambda > 0 \\ w_i \geq 0, \ \forall i \in \{1, 2, 3\} \end{cases},$$

where w_i denotes the weight of the ith indicator and λ indicates the granular information about the pairwise evaluation, which is connected to the cognitive aptitude of the experts. Setting $\lambda = 3$ and using Equation (20), the weight of risk criteria C_1, C_2, and C_3 for dimension D_1 relative to C_6 of dimension D_2 are calculated as $(0.373, 0.347, 0.280)^T$, respectively.

For quantifying the consistency of the D-CFPR based matrix R_p^T, an ID defined for the D *numbers preference relation* (as defined in Equation (21)) is used to express such inconsistency, and, for the case study taken, it is found to be consistent.

Similarly, using the same process, the priority weights of remaining criteria, shown in Figure 3 with respect to the same dimensions and criteria of other clusters (dimensions), are calculated.

Step 3: Formation of unweighted supermatrix. Arrange all priority vectors, indicating the influence of pre-set elements, in different cluster elements in the network, as sub-columns of the resultant column in an unweighted supermatrix W, which is composed of k clusters $D_k(k = 1, 2, 3)$, with corresponding linkages (*criteria*) $\{e_{k1}, e_{k2}, e_{k3}\}$ *for* $k = 1, 2, 3$. Putting $k = 1$, we get the first cluster (*dimension*) D_1 along with three elements $\{e_{11}, e_{12}, e_{13}\}$ representing three risk criteria $\{C_1, C_2, C_3\}$, respectively. For $k = 2$, we get a second cluster (*dimension*) D_2 along with three elements $\{e_{21}, e_{22}, e_{23}\}$ representing three risk criteria $\{C_4, C_5, C_6\}$. Similarly, the remaining cluster (*dimensions*) D_3, along with its risk criteria, can be found. Thus, we get three clusters (*dimensions*) $D_k = \{D_1, D_2, D_3\}$ and nine corresponding risk criteria $C_j\{j = 1, 2, \ldots, 9\}$. Based on the above, the unweighted supermatrix W is formed by placing priority vector elements in the particular column of W, where each criterion influences the other risk criteria. Details shown in Table 5.

Step 4: Calculating the weighted supermatrix. The weighted supermatrix (W^a) is calculated by multiplying unweighted supermatrix W (Table 5) by the inner dependence matrix of risk dimension $D_j(j = 1, 2, 3)$ (Table 6). Details are shown in Table 7.

Step 5: Selecting the weight of criteria based on the limit matrix. To make the matrix column stochastic in Table 7, we normalise the weighted supermatrix (W^a) column wise, and the result is shown in Table 8. The normalized weighted supermatrix $\hat{W}$ (Table 8) is raised to its limiting power using Equation (22), to get the limiting supermatrix W^q (Table 9). The final ranking of risk criteria weight for the construction project is shown in Table 10.
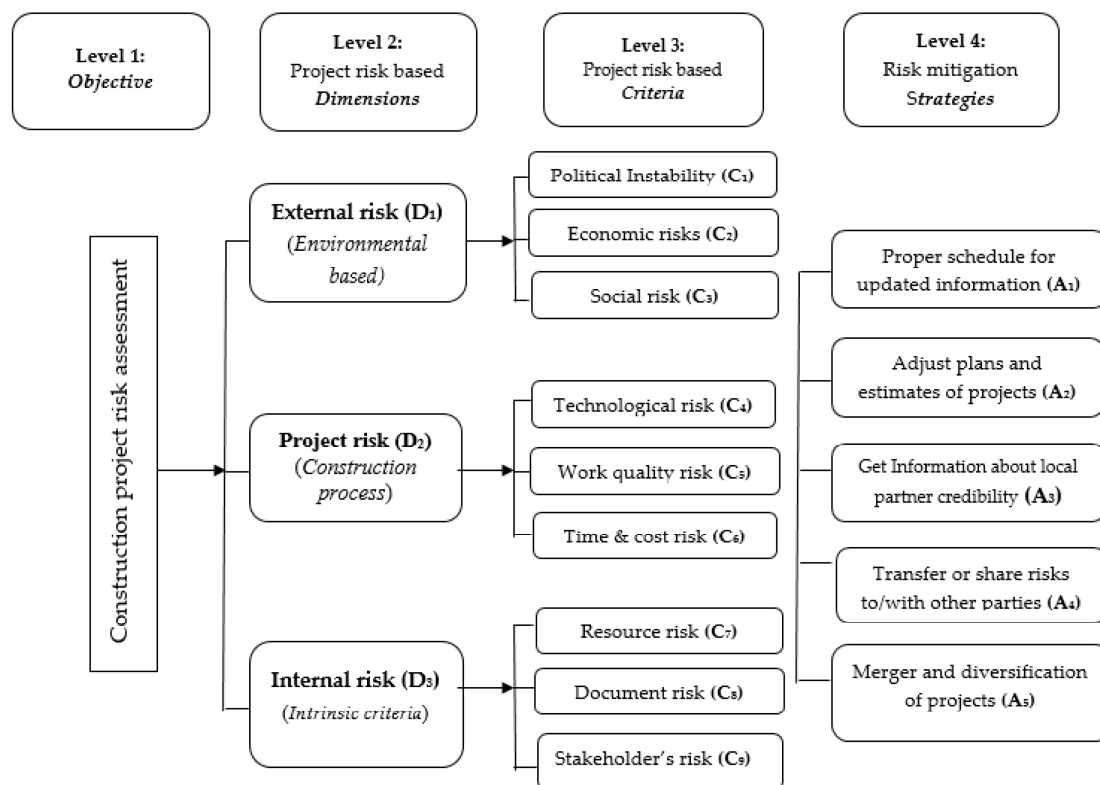

Figure 2. A hierarchical construction project risk breakdown structure.
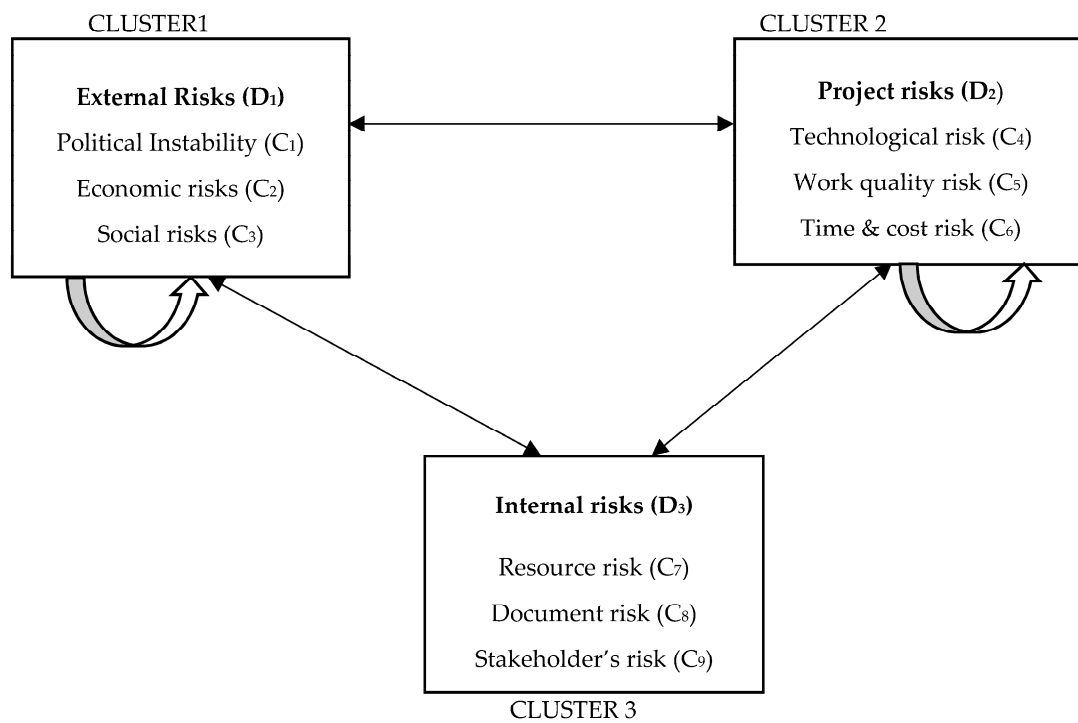
Figure 3. Network structure among construction risk dimensions and criteria.

Table 5. Unweighted supermatrix formed from every risk factor.

		External Risk (D_1)			Project Risk (D_2)			Internal Risk (D_3)		
		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
External risk (D_1)	C_1	0.000	0.576	0.589	0.315	0.386	0.373	0.332	0.353	0.395
	C_2	0.525	0.000	0.411	0.357	0.351	0.347	0.336	0.321	0.327
	C_3	0.475	0.424	0.000	0.327	0.264	0.280	0.332	0.326	0.278
Project risk (D_2)	C_4	0.288	0.355	0.354	0.000	0.461	0.510	0.348	0.346	0.340
	C_5	0.416	0.320	0.338	0.481	0.000	0.490	0.334	0.361	0.363
	C_6	0.296	0.326	0.308	0.519	0.539	0.000	0.318	0.293	0.298
Internal risk (D_3)	C_7	0.332	0.324	0.357	0.364	0.313	0.370	0.000	1.000	1.000
	C_8	0.351	0.369	0.351	0.343	0.371	0.351	1.000	0.000	1.000
	C_9	0.316	0.308	0.292	0.293	0.315	0.279	1.000	1.000	0.000

Table 6. Inner dependence matrix of construction project factors.

	Dimensions		
	External Risk	Project Risk	Internal Risk
External risk	1	0.518	0.503
Project risk	0.537	1	0.496
Internal risk	0.462	0.482	1

Table 7. Weighted supermatrix based on supply chain risk factors.

		External Risk			Project Risk			Internal Risk		
		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
External risk	C_1	0.000	0.576	0.589	0.163	0.200	0.193	0.167	0.178	0.199
	C_2	0.525	0.000	0.411	0.185	0.182	0.180	0.169	0.162	0.165
	C_3	0.475	0.424	0.000	0.170	0.137	0.145	0.167	0.164	0.140
Project risk	C_4	0.155	0.191	0.191	0.000	0.461	0.510	0.173	0.172	0.169
	C_5	0.223	0.172	0.182	0.481	0.000	0.490	0.166	0.179	0.180
	C_6	0.159	0.175	0.165	0.519	0.539	0.000	0.158	0.146	0.148
Internal risk	C_7	0.154	0.150	0.165	0.176	0.151	0.178	0.000	1.000	1.000
	C_8	0.162	0.171	0.162	0.165	0.179	0.169	1.000	0.000	1.000
	C_9	0.146	0.142	0.135	0.141	0.152	0.134	1.000	1.000	0.000

Table 8. Normalised weighted supermatrix based on supply chain risk factors.

		External Risk			Project Risk			Internal Risk		
		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
External risk	C_1	0.000	0.288	0.294	0.082	0.100	0.097	0.056	0.059	0.066
	C_2	0.263	0.000	0.206	0.093	0.091	0.090	0.056	0.054	0.055
	C_3	0.238	0.212	0.000	0.085	0.068	0.073	0.056	0.055	0.047
Project risk	C_4	0.078	0.095	0.095	0.000	0.231	0.255	0.058	0.057	0.056
	C_5	0.112	0.086	0.091	0.241	0.000	0.245	0.055	0.060	0.060
	C_6	0.079	0.088	0.083	0.260	0.270	0.000	0.053	0.049	0.049
Internal risk	C_7	0.077	0.075	0.083	0.088	0.075	0.089	0.000	0.333	0.333
	C_8	0.081	0.085	0.081	0.083	0.090	0.085	0.333	0.000	0.333
	C_9	0.073	0.071	0.068	0.071	0.076	0.067	0.333	0.333	0.000

Table 9. Limited supermatrix based on supply chain risk factors.

		External Risk			Project Risk			Disruption Risk		
		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
External risk	C_1	0.1062	0.1062	0.1062	0.1062	0.1062	0.1062	0.1062	0.1062	0.1062
	C_2	0.0958	0.0958	0.0958	0.0958	0.0958	0.0958	0.0958	0.0958	0.0958
	C_3	0.0894	0.0894	0.0894	0.0894	0.0894	0.0894	0.0894	0.0894	0.0894
Project risk	C_4	0.0972	0.0972	0.0972	0.0972	0.0972	0.0972	0.0972	0.0972	0.0972
	C_5	0.0996	0.0996	0.0996	0.0996	0.0996	0.0996	0.0996	0.0996	0.0996
	C_6	0.0971	0.0971	0.0971	0.0971	0.0971	0.0971	0.0971	0.0971	0.0971
Internal risk	C_7	0.1392	0.1392	0.1392	0.1392	0.1392	0.1392	0.1392	0.1392	0.1392
	C_8	0.1406	0.1406	0.1406	0.1406	0.1406	0.1406	0.1406	0.1406	0.1406
	C_9	0.1349	0.1349	0.1349	0.1349	0.1349	0.1349	0.1349	0.1349	0.1349

Table 10. Ranking of construction project risk criteria.

Dimensions	Risk Criteria	Ranking
External risk (D_1)	Political instability (C_1)	4
	Economic risk (C_2)	8
	Social risk (C_3)	9
Project risk (D_2)	Technological risk (C_4)	6
	Work quality risk (C_5)	5
	Time and cost risk (C_6)	7
Internal risk (D_3)	Resource risk (C_7)	2
	Document and information risk (C_8)	1
	Stakeholder's risk (C_9)	3

From Table 10, it is concluded that the third cluster (dimension) *internal risk* (D_3) has a severe risk effect on the construction project sector. *Document and information risk* (C_8) is the most risky, followed by *resource risk* (C_7) and *stakeholder's risk* (C_9). First cluster *External risk* (D_1) has less of a risk effect on construction business. *Economic risk* (C_2) and *social risk* (C_3) are in the 8th and 9th positions, respectively. However, *political instability* attains the 4th position in respect to the risk category. Managers and stakeholders should keep this in view when choosing projects in large construction sectors.

5.3. Determination of Final Alternative Ranking by D-MABAC

In this phase, the evaluation and ranking of risk response alternatives is performed by the application of a D numbers based MABAC (D-MABAC) methodology in construction project risk management. The step-by-step computational procedure is shown below.

Step 1: First, the five *risk response* alternative vectors, with respect to nine risk criteria $C_j (j = 1, 2, \ldots, 9)$, are represented as $A_i = (d_{i1}, d_{i2}, \ldots, d_{i9})$ $(i = 1, 2, \ldots, 5)$ using *incomplete and uncertain* numbers expressed in D numbers. Using Equations (23) and (24), we develop an initial decision matrix $M = [d_{ij}]_{5 \times 9}$ (Table 11) along with its crisp form $X = [I(d_{ij})]_{5 \times 9} = [x_{ij}]_{5 \times 9}$.

Table 11. Comparison of alternatives w.r.t risk criteria using D numbers.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	(0.62, 0.5)	(0.72, 0.4), (0.48, 0.6)	(0.53, 0.4)	(0.58, 0.5)	(0.72, 0.6)	(0.48, 0.6), (0.64, 0.4)	(0.66, 0.6)	(0.38, 0.9)	(0.84, 0.2)
A_2	(0.68, 0.4)	(0.44, 0.8)	(0.64, 0.6), (0.32, 0.3)	(0.44,.9)	(0.82, 0.9)	(0.88, 0.6)	(0.56, 0.8)	(0.92, 0.8)	(0.69, 0.4)
A_3	(0.54, 0.8), (0.68, 0.2)	(0.68, 0.3)	(0.47, 0.9)	(0.78, 0.8)	(0.38, 0.7), (0.59, 0.3)	(0.68, 0.5)	(0.29, 0.6), (0.39, 0.4)	(0.28, 0.6)	(0.34, 0.6)
A_4	(0.72, 0.9)	(0.49, 0.7)	(0.78, 0.4)	(0.86, 0.4)	(0.88, 0.4)	(0.47, 0.7)	(0.64, 0.2)	(0.62, 1)	(0.56, 0.7)
A_5	(0.48, 1)	(0.56, 0.9)	(0.82, 0.7)	(0.36, 1)	(0.78, 0.7)	(0.59, 0.9)	(0.78, 0.7)	(0.68, 0.3), (0.49, 0.6)	(0.44, 0.8)

Step 2: The elements of the crisp decision matrix $X = [x_{ij}]_{5 \times 9}$ are normalized using Equations (24) and (25) to form a normalized decision matrix $N = [t_{ij}]_{5 \times 9}$, shown in Table 12.

Table 12. Normalised decision matrix of alternatives w.r.t criteria.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	0.8989	0	1	1	0.7927	0	0.3589	0.5846	1
A_2	1	0.6022	0.2597	0.6826	0	0.0744	0.2344	0	0.5179
A_3	0.2128	1	0.4171	0	0.7642	0.9488	0.5167	0.8427	0.8393
A_4	0	0.6263	0.7238	0.8383	1	1	1	1	0
A_5	0.4468	0.1935	0	0.7904	0.4974	0.0605	0	0.3531	0.1786

Step 3: Using Equations (26) and (27), the elements of the weighted normalized decision matrix $V = [v_{ij}]_{5 \times 9}$ are calculated, and are shown in Table 13.

Table 13. Weighted normalised decision matrix of alternatives w.r.t criteria.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	0.2017	0.1916	0.1788	0.1944	0.1786	0.0971	0.1892	0.2381	0.2698
A_2	0.2124	0.1304	0.1126	0.1636	0.0996	0.1043	0.1718	0.1406	0.2048
A_3	0.1288	0.1641	0.1267	0.0972	0.1757	0.1892	0.2111	0.2812	0.2481
A_4	0.1062	0.1324	0.1541	0.1787	0.1992	0.1942	0.2784	0.1693	0.1349
A_5	0.1537	0.0958	0.0894	0.1740	0.1491	0.1030	0.1392	0.1995	0.1590

Step 4: Next, using Equations (28) and (29), we determine the BAA, $G = [g_1\ g_2\ \ldots\ g_9]$ for each criterion $C_j (j = 1, 2, \ldots, 9)$. This is followed by calculation of the distance (q_{ij}) for matrix elements $Q = [q_{ij}]_{5 \times 9}$ for risk response alternatives $A_i (i = 1, 2, \ldots, 5)$ from BAA $G = [g_1\ g_2\ \ldots\ g_9]$ using Equations (30) and (31).

Step 5: Finally, using Equation (32), we calculate the sum function $\hat{S}_i (i = 1, 2, \ldots, 5)$ to obtain the ranking of alternatives $A_i (i = 1, 2, \ldots, 5)$. A graphical representation of the process is shown in Figure 4. Ranking of alternative risk response alternatives (Table 14) is finalised according to values calculated by D-MABAC in descending order. In this paper, the first alternative risk response was selected and implemented.
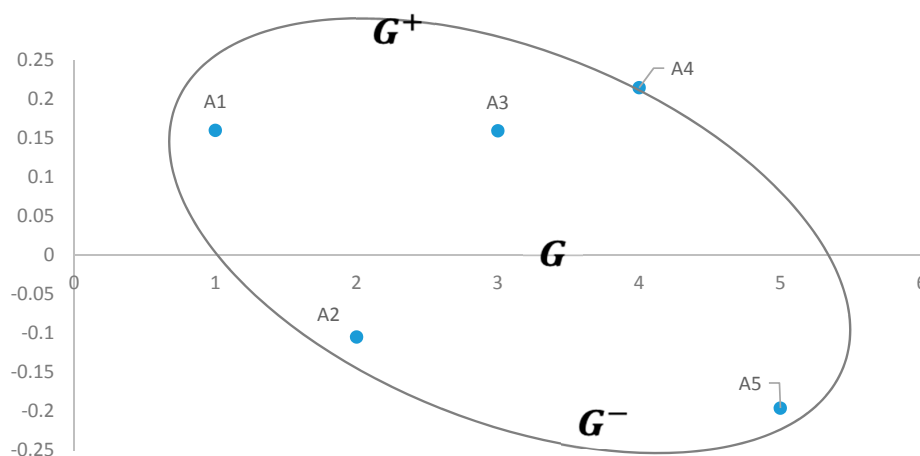
Figure 4. D numbers based Multi-Attributive Border Approximation area Comparison (D-MABAC) in risk mitigation strategy selection.

Table 14. Ranking of alternatives using the D-MABAC method.

	Alternative Risk Responses	**Q**	**Rank**
Risk response (A_1)	Proper scheduling for getting updated project information.	0.2830	1
Risk response (A_2)	Adjust plans for scope of work and estimates to counter risk implications.	-0.1161	4
Risk response (A_3)	Get information about local partner's credibility from its present and past business partners.	0.1660	2
Risk response (A_4)	Transfer or share risks to/with other parties.	0.0913	3
Risk response (A_5)	Merger and diversification of projects.	-0.1935	5

6. Results and Discussion

In this section, a detailed comparative analysis of all alternative initiatives (with respect to criteria and dimensions) is conducted.

6.1. Comparison of Alternative Ranking Using Different MCDM Methods

The hybrid MCDM methods in D numbers environment namely, D numbers based multi-attributive border approximation area comparison (D-MABAC), and D numbers based technique for order of preference by similarity to ideal solution (D-TOPSIS), D numbers based complex proportional assessment (D-COPRAS), and D numbers based additive ratio assessment (D-ARAS), were applied to the construction project based case study data to obtain the weighted normalised decision-making matrix $V = [v_{ij}]_{5 \times 9}$ (Table 13). The priority order of the risk response alternatives $A_i (i = 1, 2, \ldots, 5)$ is compared and presented in Table 15.

Table 15. Comparison of MABAC with various existing multi-criteria decision making methods.

Alternative Risk Responses	D-MABAC	D-TOPSIS	D-COPRAS	D-ARAS
A_1	1	1	1	1
A_2	4	4	4	4
A_3	2	2	2	2
A_4	3	3	3	3
A_5	5	5	5	5

Ranking of the risk response alternatives according to the presented MCDM methods concluded that the optimal alternative risk response is A_1 (Proper scheduling for getting updated project information), followed by A_3 (Information about local partner's credibility), A_4 (Transfer risks with other parties), and A_2 (Adjust plans for scope of work). The worst performing risk response alternative is A_5 (Merger and diversification of projects).

Spearman's rank correlation coefficient (r_k) between ranks is applied for determining correlation of ranks obtained by various approaches. Here, this coefficient is applied to demonstrate the statistical importance of difference among the ranking obtained through pairwise correlation analysis of different MCDM methods. Based on the recommendation of Keshavarz Ghorabaee et al. [65], all (r_k) values higher than 0.80 show considerably high correlation. As per Table 16, a strong correlation (1.000) among the MCDM approaches is shown, confirming the credibility of the proposed approach.

Table 16. Rank correlation of various MCDM methods.

Spearman's Coefficient	D-MABAC	D-TOPSIS	D-COPRAS	D-ARAS
r_k	-	1.000	1.000	1.000

6.2. Sensitivity Analysis

Ranking of results in MCDM problems are subject to the distribution of weight coefficients of the criteria. Sometimes, modifying these criteria weight coefficients may change the ranking order of alternatives, generally analysed by sensitivity analysis during the decision-making process. The above weight coefficients are usually based on expert subjective perception, and thus the outcome of probable deviation of these weight values need to be properly assessed.

A sensitivity analysis was executed to measure the level of crosstalk amongst the criteria, revealing the variation in alternative rankings with variation in criteria weight. Outcomes of the sensitivity analysis for prioritising specific project based criteria $C_j (j = 1, 2, \dots, 9)$ weights are shown in Table 17, and its corresponding effect on ranking of risk response alternatives $A_i (i = 1, 2, \dots, 5)$ in Table 18.

- The results (Table 17 and Figure 5) shows that assigning various weights to project based criteria $C_j (j = 1, 2, \dots, 9)$ through different scenarios $\{S_1 - S_8\}$ results in changes to ranking of individual alternatives, thus proving that the model is sensitive to variations in weight coefficients.

- Analysis of the alternative ranking through eight scenarios (Table 18) showed that alternative A_1 retained its rank in five scenarios $\{S_2, S_3, S_4, S_5, S_8\}$ *(best-ranked alternative)*, while, in the remaining two scenarios $\{S_1, S_7\}$, it was ranked second, and third in scenario $\{S_6\}$.

- The worst-ranked alternative A_5 retained its rank in six scenarios $\{S_2, S_3, S_4, S_5, S_7, S_8\}$, while in two scenarios $\{S_1, S_6\}$, it was ranked second worst. Therefore, changing the criteria weights through different scenarios resulted in changes to the ranks of the remaining alternatives.

- In addition, from Tables 17 and 18, it is clear that prioritising criteria C_9 has less of an effect on ranking position of alternatives. However, prioritising criteria set $\{C_4, C_6, \text{and } C_7\}$ in scenario S_7, $\{C_2, C_6, \text{and } C_8\}$ in scenario S_1, along with $\{C_4, C_6, \text{and } C_8\}$ in scenario S_6, all altered the positions of risk response alternatives $A_i (i = 1, 2, \dots, 5)$.

- The prioritising of criteria weight in scenarios $\{S_2, S_3, S_4, S_5, S_8\}$ has no effect on ranking of best or worst risk response alternative A_1 and A_5, respectively, but it does have an effect on the ranking of the second best risk response alternative A_2.
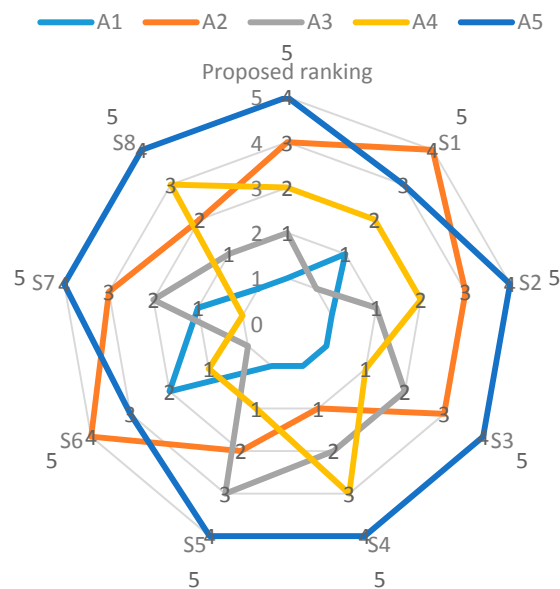

Figure 5. Sensivity analysis of the alternative ranking through different scenarios.

Table 17. Scenarios for different criteria weights.

Criteria	Scenarios *							
	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8
C_1	0.0113	0.1482	0.0226	**0.2674**	**0.1944**	**0.0795**	0.0081	**0.1602**
C_2	**0.1578**	0.1121	0.1204	0.1178	0.0914	0.0632	0.0962	0.0537
C_3	0.0576	**0.1789**	**0.2946**	0.0001	**0.1853**	0.0577	0.0308	0.1054
C_4	0.0904	0.1118	**0.2655**	**0.1556**	**0.2219**	0.0519	**0.2032**	0.0958
C_5	0.1172	0.0033	0.0478	0.0598	0.0603	0.0703	0.0875	**0.1805**
C_6	**0.2016**	0.0233	0.0496	0.0631	0.0322	**0.3311**	**0.1958**	0.0218
C_7	0.0894	**0.1663**	0.0352	0.0937	0.056	0.0055	**0.1485**	0.0223
C_8	**0.2103**	0.0933	0.003	0.0276	0.0871	**0.332**	0.1191	0.0539
C_9	0.0645	**0.1628**	**0.1613**	**0.215**	0.0714	0.0089	0.1107	**0.3063**

* Priority criteria are indicated in bold text for different scenarios.

Table 18. Sensitivity in alternative rankings for different scenarios of criteria weighting.

Alternative Risk Responses	Scenarios							
	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8
A_1	2	1	1	1	1	3	2	1
A_2	5	4	4	2	3	5	4	3
A_3	1	2	3	3	4	1	3	2
A_4	3	3	2	4	2	2	1	4
A_5	4	5	5	5	5	4	5	5

7. Conclusions

Construction projects present a very complex field involving a large number of stakeholders. From the perspective of information sharing, uncertain information and data cause loss of faith among various stakeholders and increased risk in construction management, including project

complexity and decision-making environment conditions. These risks affect project activities, which indirectly impact construction costs, resulting in delays and poor building quality. Thus, in this paper, we rank uncertain risk strategies in construction projects using a D-ANP-MABAC multi-criteria decision-making (MCDM) approach. In the new proposed method, the decision matrix determination from the MCDM problem is transformed to D numbers, which effectively represent the inevitable uncertainties such as incompleteness and imprecision, due to the subjective assessment of decision makers. As the basic element of many decision-making methods especially in analytic network process (ANP) model, the preference relation has attracted interests among researchers and practitioners. Fuzzy preference relation construct pairwise decision matrices based on linguistic values but is inconsistent due to inability of experts in dealing with overcomplicated objects. CFPR methodology [30] removes this inconsistency, but fails to deals with incomplete and uncertain information due to the lack of experts' knowledge and the limitation of cognition. To overcome this weakness, D-CFPR methodology is applied to decision matrices allowing all stakeholders (members) of a construction business to address multiple criteria involving various types of uncertainties, such as imprecision and fuzziness in the decision process. The D-CFPR uses D numbers to express the linguistic preference values given by experts, and it can also be reduced to classical CFPR. Based on the D-CFPR based preference relation, the priority vectors of criteria are determined, to be used as inputs for any cluster of matrix formed by the D-ANP method, and obtain the corresponding risk criteria weights. The alternative risk response strategy ranking is achieved using the D-MABAC method.

In view of several categories of uncertainties, including incompleteness and impreciseness, the proposed technique can effectively represent and address uncertain information weighting risk criteria and alternatives in a logical way. An example of selecting risk strategies in construction risk projects is shown here to demonstrate the efficiency of the proposed approach. The assessment of a real world application of D-ANP-MABAC methodology, along with its output result of sensitivity, clearly identifies its potential to provide stable solutions to the problematic choice of laying-up positions. Based on that, the proposed risk strategy alternatives are successfully ranked. Thus, it can be concluded that the above procedure has provided an alternate approach for sustainable risk analysis and decision-making in the construction sector. In our proposed method, we consider both CFPR and ANP methodologies in D numbers domain. As in the present scenario, since the priority vectors for the criteria set are deduced from D-CFPR methodology, which are used as inputs in ANP matrix, it will thus also consume more computational time. Therefore, the computational complexity occurring in present D-CFPR-ANP methodology in future studies needs to be further optimized. In future research, the theoretical framework needs to be modified considering the hidden risks in construction sectors and further be applied to other real-life application areas such as supplier selection problems, project portfolio management, renewable energy selection, etc., to further validate its effectiveness.

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