Journal of Urban Development and Management
https://www.acadlore.com/journals/JUDM

Enhancing Urban Development with Picture Fuzzy Sets: A Strategic Decision Support Framework

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Received: 11-05-2023 **Revised:** 12-17-2023 **Accepted:** 12-23-2023

Citation: T. Shahid, S. Ashraf, and D.S. Mashat, "Enhancing urban development with Picture Fuzzy Sets: A strategic decision support framework," *J. Urban Dev. Manag.*, vol. 2, no. 4, pp. 172–180, 2023. https://doi.org/10.56578/judm020401.

Abstract: In the realm of sustainable urban development, a paramount focus is placed on the amalgamation of environmental conservation, the integration of smart technology, and the promotion of social inclusivity. This approach advocates for transit-oriented development, the establishment of resilient infrastructure, and the active engagement of communities. A critical balance is sought between economic viability and adaptive governance, aiming to cultivate cities that are simultaneously environmentally conscious, economically vibrant, and socially equitable. Within this context, Multiple Attribute Decision Making (MADM) emerges as a pivotal tool, streamlining decision processes through the quantitative evaluation of alternatives against criteria such as environmental impact and social inclusivity. MADM plays an instrumental role in ensuring effective resource allocation, thereby fostering resilient infrastructure and optimizing the equilibrium between economic growth and sustainability in urban planning. This study delves into an advanced methodology for addressing uncertainties in decision-making, employing Picture Fuzzy Sets (PFSs), articulated through the meticulous application of the Measurement Alternatives and Ranking according to Compromise Solution (MARCOS). The utilization of the MARCOS strategy in decision-making is underscored by its proven robustness as a tool for pinpointing the optimal objective. This method integrates diverse aggregation strategies to adeptly navigate complex decision scenarios characterized by multiple criteria. To illustrate the adaptability and efficacy of the proposed methodology, a numerical case study is presented, offering a vivid demonstration of its practical application in the field of urban development.

Keywords: Picture Fuzzy Sets; Decision-making; MARCOS; Urban development

1 Introduction

Sustainable urban development involves a holistic approach that integrates economic, social, and environmental considerations. This includes prioritizing environmental conservation, leveraging smart infrastructure and technology, and promoting social inclusivity. Transit-oriented development encourages efficient mobility, while resilient infrastructure is vital for long-term sustainability. Engaging communities, balancing economic viability, and maintaining adaptive governance structures are key elements. Continuous monitoring and evaluation ensure that urban development strategies remain responsive and effective, ultimately creating cities that are environmentally conscious, economically vibrant, and socially equitable. It, coupled with MADM, forms a potent framework for navigating complex choices in city planning. MADM enhances the decision-making process by systematically evaluating alternatives based on various criteria, such as environmental impact, economic viability, and social inclusivity. Integrating MADM into sustainable urban development allows for a more quantitative and data-driven approach, ensuring that decisions align with the city's overarching goals. This synergy promotes effective resource allocation, fosters resilient infrastructure, and optimizes the balance between economic growth and social and environmental considerations. In essence, MADM becomes a valuable tool in shaping cities that are not only sustainable but also well-aligned with the diverse needs and priorities of their inhabitants.

The significance of MADM in this context extends beyond its capacity for systematic analysis. It serves as a catalyst for optimizing decision outcomes, promoting efficiency, and enhancing the overall effectiveness of response plans. As we delve into the integration of PFSs and algebraic operations within the MADM framework, we anticipate unlocking a transformative tool that not only acknowledges the complexities of earthquake response planning but also provides actionable insights for decision-makers. This research endeavors to demonstrate the unparalleled utility of MADM in this critical domain, underscoring its role as the linchpin for informed and effective decision-making in the face of seismic uncertainties.

Since its introduction by Zadeh [1], fuzzy set theory (FST) has been extensively employed to simulate uncertainty that arises in practical applications. Numerous investigators have paid attention to the generalization of FST and its applications. Among several generalizations of fuzzy sets, Çoker and Atanassov [2, 3] developed the idea of intuitionistic fuzzy sets (IFSs), which has proven to be a very helpful tool for dealing with vagueness. IFS was introduced, reflecting the fact that the degree of non-membership is not always equal to one minus the degree of membership, by adding the degree of non-membership to the fuzzy set. Interval-valued IFSs are defined by a membership function, a non-membership function, and a hesitancy function whose values are intervals. This concept was introduced by Atanassov [4, 5]. Thus, there are some situations where IFS and interval-valued IFS theory offer a robust and appropriate framework to address missing information found in real-world decision-making situations. Bustince et al. [6–8] recently suggested the PFS and looked into some of its fundamental functions and characteristics. The PFS is described by three functions expressing the degree of membership (κ), the degree of neutral membership(δ), and the degree of non-membership(ξ). One restriction is that $\kappa+\delta+\xi \leq 1$. In general, PFS-based models can be used in scenarios where human judgment is needed and there are multiple answer options—yes, abstain, no, and refusal—that are difficult to adequately convey in conventional FS and IFS models. Research on the PFS idea has advanced to some extent thus far. Singh [9] examined the correlation value for PFS and applied the correlation value to clustering analysis with PF information. Son [10] provides a number of cutting-edge fuzzy clustering techniques based on image fuzzy sets and their applications to weather and time series forecasting. Thong and Son [11] and Thong and Son [12] created a novel hybrid model for medical diagnosis and application to health care support systems that combines intuitionistic fuzzy recommender systems with PF clustering. Nevertheless, Atanassov's intuitionistic FST has been effectively implemented in different areas. However, real-life scenarios exist, which are represented by Atanassov's IFSs. One notable example of such a scenario is voting, where voters can be classified into four groups: those who vote in favor of, those who abstain from, and those who refuse to vote.

In general, models based on PFS [13] may be suitable for dealing with human opinions that involve a greater number of responses of the following type: yes, abstain, no, and refuse. Therefore, in order to deal with these types of situations, in this paper we introduce the concept of similarity measures for PFS, which is a new extension of the similarity measure of Atanassov's IFS. The remainder of this paper is organized as follows in order to do this: We present some fundamental ideas on interval-valued IFSs, PFSs, and IFSs in the next section.

Expanding the application domains, the study [14] extended the TOPSIS method with PFSs. There are many other techniques with PFSs, like the TODIM method [15], the Vikor method [16], the COCOSO method [17], the MOORA method [18], and the REGIME method [19]. These techniques highlight the versatility and effectiveness of PFSs in diverse decision-making scenarios.

The paper is structured as follows: The introductory section provides an overview of the study. In Section 2, we delve into fundamental concepts essential for comprehending the subsequent content. Section 3 introduces a novel methodology for PFS. Following that, Section 4 presents and discusses a case study on urban development and management. Finally, Section 5 serves as the conclusion, summarizing the key findings of the article.

2 Preliminaries

In this section, we'll explore pivotal topics crucial to crafting this article, delving into their significance and impact.

Definition 2.1 [20] A PFS $\gimel$ on a Γ universe is an entity that takes the form of

$$\gimel = \{(\varsigma, \kappa_{\gimel}(\varsigma), \delta_{\gimel}(\varsigma), \xi_{\gimel}(\varsigma)) \mid \varsigma \in \Gamma\} \tag{1}$$

where, $\kappa_{\gimel}(\varsigma) \in [0,1]$ is called the membership, $\delta_{\gimel}(\varsigma) \in [0,1]$ is called the neutral membership and $\xi_{\gimel}(\varsigma) \in [0,1]$ is called the membership, and where $\kappa_{\gimel}$, $\delta_{\gimel}$ and $\xi_{\gimel}$ satisfy the following condition:

$$(\forall \varsigma \in \Gamma)\,(\kappa_{\gimel}(\varsigma) + \delta_{\gimel}(\varsigma) + \xi_{\gimel}(\varsigma) \leq 1) \tag{2}$$

Definition 2.2 [21] Assume $\gimel_1 = (\varsigma, \kappa_{\gimel_1}(\varsigma), \delta_{\gimel_1}(\varsigma), \xi_{\gimel_1}(\varsigma))$ and $\gimel_2 = (\varsigma, \kappa_{\gimel_2}(\varsigma), \delta_{\gimel_2}(\varsigma), \xi_{\gimel_2}(\varsigma))$ be PFSs. The basic operational laws can be written as follows:

· $\gimel_1 \bigcup \gimel_2 = \{(\varsigma, \max(\kappa_{\gimel_1}(\varsigma), \kappa_{\gimel_2}(\varsigma)), \min(\delta_{\gimel_1}(\varsigma), \delta_{\gimel_2}(\varsigma)), \min(\xi_{\gimel_1}(\varsigma), \xi_{\gimel_2}(\varsigma)) \mid \varsigma \in \Gamma\}$

· $\gimel_1 \bigcap \gimel_2 = \{(\varsigma, \min(\kappa_{\gimel_1}(\varsigma), \kappa_{\gimel_2}(\varsigma)), \min(\delta_{\gimel_1}(\varsigma), \delta_{\gimel_2}(\varsigma)), \max(\xi_{\gimel_1}(\varsigma), \xi_{\gimel_2}(\varsigma)) \mid \varsigma \in \Gamma\}$

$\cdot\, Co(\daleth) = \{(\xi_\daleth(\varsigma), \delta_\daleth(\varsigma), \kappa_\daleth(\varsigma)) \mid \varsigma \in \Gamma\}$

Definition 2.3 [22] Let $\daleth_1 = (\varsigma, \kappa_{\daleth_1}(\varsigma), \delta_{\daleth_1}(\varsigma), \xi_{\daleth_1}(\varsigma))$ and $\daleth_2 = (\varsigma, \kappa_{\daleth_2}(\varsigma), \delta_{\daleth_2}(\varsigma), \xi_{\daleth_2}(\varsigma))$ be PFSs, then the distance $d(\daleth_1, \daleth_2)$ between $\daleth_1$ and $\daleth_2$ is defined as follows:

$$d(\daleth_1, \daleth_2) = |\kappa_{\daleth_1}(\varsigma) - \kappa_{\daleth_2}(\varsigma)| + |\delta_{\daleth_1}(\varsigma) - \delta_{\daleth_2}(\varsigma)| + |\xi_{\daleth_1}(\varsigma) - \xi_{\daleth_2}(\varsigma)| \tag{3}$$

3 Methodology of PFS-MARCOS for Addressing MADM Issues

This section aims to devise an innovative picture fuzzy MARCOS decision method for addressing the MADM problem characterized by decision information in the form of PFSs. The suggested technique focuses on applying the MARCOS technique to establish the priority order of schemes.

To enhance the precision and rationality of decision analysis in uncertain scenarios, the proposed method integrates these models with PFS. The steps of the new PFS-MARCOS method are shown in Figure 1. This shows the organized way it is used to make decisions that are more accurate and make sense when things are uncertain.

3.1 Construction of a Comprehensive Decision Matrix Incorporating PFS for Decision-Making

This section examines the incorporation of PFS with a MADM technique to tackle inherent ambiguity. To achieve ideal outcomes, it is necessary to meticulously choose the most efficacious solutions. Algorithms are essential in this research, functioning as instruments for methodical decision-making. An algorithm, in this sense, refers to a systematic and planned sequence of procedures that is specifically designed to produce the optimal solution for a certain problem.

Algorithm

1. Decision matrix by the expert.
2. The normalized matrix for cost type data by interchanging the positive membership with negative membership.
3. Evaluate an expanded initial DM by evaluating the PLT-PIS and PLT-NIS.
$$PIS = max\varepsilon_{ij} \tag{4}$$
$$NIS = min\varepsilon_{ij} \tag{5}$$
4. Compute the distance for PIS and NIS by using Definition 2.3.
5. Closeness coefficient: Utilizing ξ_{ij}^{+} and ξ_{ij}^{-}, determine the closeness coefficient as follows:
$$\mathfrak{C}_{ij} = \frac{\xi_{ij}^{-}}{\xi_{ij}^{-} + \xi_{ij}^{+}} \tag{6}$$
6. Extended decision matrix: Create an expanded decision matrix by incorporating $\mathfrak{C}ij$, along with the anti-ideal $(\mathfrak{A}^{-} = \mathfrak{C}i1^{-}, \mathfrak{C}i2^{-}, ..., \mathfrak{C}in^{-})$ and ideal $(\mathfrak{A}^{+} = \mathfrak{C}_{ij}^{+}; j = 1, 2, ..., n)$ solutions.
$$\mathfrak{A} = \begin{pmatrix} \mathfrak{C}_{i1}^{-} & \mathfrak{C}_{i2}^{-} & \dots & \mathfrak{C}_{in}^{-} \\ \mathfrak{C}_{11} & \mathfrak{C}_{12} & \dots & \mathfrak{C}_{1n} \\ \mathfrak{C}_{21} & \mathfrak{C}_{22} & \dots & \mathfrak{C}_{2n} \\ \vdots & \vdots & \dots & \vdots \\ \mathfrak{C}_{m1} & \mathfrak{C}_{m2} & \dots & \mathfrak{C}_{mn} \\ \mathfrak{C}_{i1}^{+} & \mathfrak{C}_{i2}^{+} & \dots & \mathfrak{C}_{in}^{+} \end{pmatrix} \tag{7}$$
Here
$$\mathfrak{C}_{ij}^{-} = min\mathfrak{C}_{ij} \tag{8}$$
and
$$\mathfrak{C}_{ij}^{-} = max\mathfrak{C}_{ij} \tag{9}$$

7. Normalization: Apply the given equation to the extended decision matrix E to convert it into its normalised version, which is $E = [n_{ij}]_{(m+2)\times n}$.

$$n_{ij} = \frac{\mathfrak{C}_{ij}}{\mathfrak{C}_{ij}^{+}} \tag{10}$$

where, $\mathfrak{C}_{ij}$ and $\mathfrak{C}_{ij}^{+}$ are the components of the matrix E.

8. Weighted decision matrix: Construct the ultimate weighted DM F, represented by the equation below:

$$f_{ij} = n_{ij} \times \nabla_j \tag{11}$$

In the context where n_{ij} constitutes an element within the matrix $E^{'}$, and ∇_j represents the weight assigned to the j-th criterion.

9. Degree of utility of alternatives: Assess the degree of utility for alternatives $\mathfrak{U}_i$ through the application of the following equations:

$$\mathfrak{U}_i^{-} = \frac{\mathfrak{S}_i}{\mathfrak{S}^{-}} \tag{12}$$

$$\mathfrak{U}_i^{+} = \frac{\mathfrak{S}_i}{\mathfrak{S}^{+}} \tag{13}$$

where, $\mathfrak{S}_i = \sum\limits_{j=1}^{n} f_{(i+1)j}(i = 1, 2, ..., m)$, $\mathfrak{S}^{-} = \sum\limits_{j=1}^{n} f_{1j}$ and $\mathfrak{S}^{+} = \sum\limits_{j=1}^{n} f_{(m+2)j}$.

10. Utility function: Calculate the utility function for alternatives $F(\mathfrak{U}_i)$ using the provided equation.

$$F(\mathfrak{U}_i) = \frac{\mathfrak{U}_i^{+} + \mathfrak{U}_i^{-}}{1 + \frac{1-F(\mathfrak{U}_i^{+})}{F(\mathfrak{U}_i^{+})} + \frac{1-F(\mathfrak{U}_i^{-})}{F(\mathfrak{U}_i^{-})}} \tag{14}$$

In cases where the utility function is defined in terms of the ideal $F(\mathfrak{U}i^{+})$ and contrary to ideal $F(\mathfrak{U}i^{-})$, their respective formulations are provided by the following expressions:

$$F(\mathfrak{U}_i^{+}) = \frac{\mathfrak{U}_i^{-}}{\mathfrak{U}_i^{+} + \mathfrak{U}_i^{-}} \tag{15}$$

$$F(\mathfrak{U}_i^{-}) = \frac{\mathfrak{U}_i^{+}}{\mathfrak{U}_i^{+} + \mathfrak{U}_i^{-}} \tag{16}$$

11. Ranking: Order the alternatives according to their values in the utility function. It is preferable for an alternative to possess the highest attainable utility function value.

Flowchart of the algorithm of MARCOS method is given in Figure 1.

4 Case Study: Sustainable Urban Development and Management

In the rapidly changing urban environment of Metropolis, the increasing speed of urbanization necessitates a deliberate and planned approach to sustainable development and management.As the city experiences rapid growth, the local administration must navigate the complex task of balancing development with environmental preservation, economic stability, and social fairness.The primary objective is to shape an urban environment that not only prospers financially but also serves as a symbol of environmental awareness and social inclusiveness.

This case study examines four distinct solutions presented for the sustainable urban growth and management of Metropolis, each giving a different vision for the future of the city. Each alternative presents a clear and unique vision of Metropolis's potential future, ranging from a strong dedication to ecological preservation to the adoption of advanced smart city solutions and a focus on social equality.The evaluation criteria include the factors of environmental effect, economic viability, social equality, and infrastructural resilience, creating a comprehensive framework that takes into account the various aspects of sustainable urban development.

During the upcoming investigation, we will thoroughly examine the complexities of each option, carefully analyzing their subtle differences and consequences.The objective is to reveal the approach that effectively manages the intricacies of urban expansion while simultaneously establishing Metropolis as a symbol of sustainability, resilience, and inclusivity.The exploration of many options and the assessment of relevant factors establishes the basis for a prudent decision-making process, guaranteeing that Metropolis develops into a city that not only prospers in the present but also serves as an exemplar for future cities.

The case study's criteria are as follows:

1. Environmental Impact($\mathfrak{C}_1$)**:** Assess the alternatives based on their impact on air and water quality, biodiversity, and overall environmental sustainability.

2. Economic Viability($\mathfrak{C}_2$)**:** Evaluate the economic feasibility of each alternative, considering factors such as construction costs, job creation, and long-term economic growth.

3. Social Equity($\mathfrak{C}_4$)**:** Examine the inclusivity of each alternative, assessing its impact on social cohesion, affordable housing, and access to essential services for all residents.

4. Infrastructure Resilience($\mathfrak{C}_4$)**:** Analyze the resilience of the proposed infrastructure in the face of natural disasters, climate change, and other external shocks.

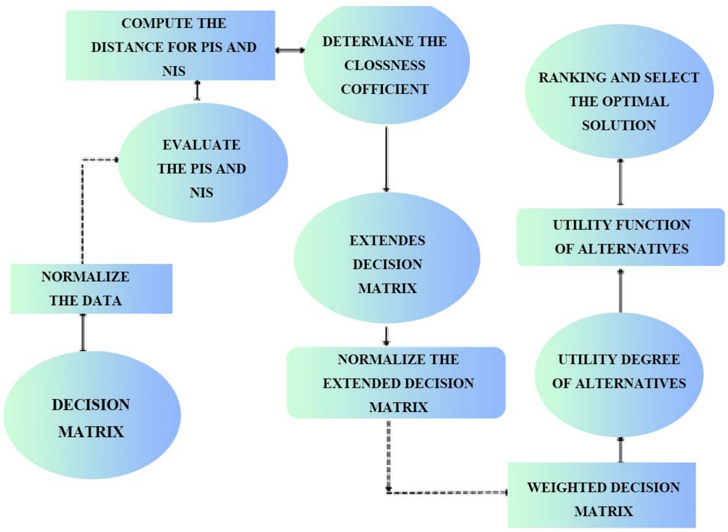

Figure 1. Flow chart of MARCOS algorithm

Examine particular criteria for earthquake reaction in comparison to other options.

1. Eco-Centric Development($\mathfrak{D}_1$)**:** This approach focuses on preserving and enhancing the city's natural ecosystems. It involves strict land-use regulations, green corridors, and sustainable architecture to minimize environmental impact. The emphasis is on biodiversity, clean energy, and efficient waste management.

2. Transit-Oriented Development (TOD)($\mathfrak{D}_2$)**:** TOD promotes compact, mixed-use development centered around public transportation hubs. This alternative aims to reduce reliance on private vehicles, decrease traffic congestion, and enhance walkability. It includes the development of affordable housing near transit nodes to create vibrant, accessible communities.

3. Smart City Solutions($\mathfrak{D}_3$)**:** This approach leverages technology and data to optimize urban services, resource usage, and citizen engagement. Smart infrastructure, efficient energy management, and digital governance systems are key components. The goal is to enhance the quality of life, improve resource efficiency, and foster innovation.

4. Socially Inclusive Development($\mathfrak{D}_4$)**:** This alternative prioritizes social equity and inclusivity. It involves the creation of affordable housing, community spaces, and social amenities to address the needs of diverse populations. The focus is on reducing inequality, fostering community cohesion, and ensuring that development benefits all residents.

Presented below is the step-by-step computing process detailed for the stated MCDM problem.

Step 1. Involves the creation of decision matrices by the expert, as shown in Table 1.

Table 1. Decision matrix by the expert

Alternatives	$\mathfrak{A}_1$	$\mathfrak{A}_2$	$\mathfrak{A}_3$	$\mathfrak{A}_4$
$\mathfrak{D}_1$	0.2,0.4,0.3	0.7,0.1,0.1	0.2,0.5,0.2	0.3,0.5,0.2
$\mathfrak{D}_2$	0.1,0.5,0.2	0.6,0.1,0.2	0.1,0.6,0.3	0.5,0.1,0.1
$\mathfrak{D}_3$	0.6,0.2,0.2	0.1,0.5,0.3	0.4,0.1,0.2	0.4,0.3,0.2
$\mathfrak{D}_4$	0.4,0.6,0.1	0.3,0.3,0.2	0.5,0.2,0.1	0.6,0.2,0.1

Step 2. Normalizing the matrix is unnecessary due to the nature of the benefit type data.

Step 3. Involves assessing an expanded initial PF DM by quantifying the PF-PIS and PF-NIS utilizing equations (29,30). Results are shown in Table 2 and Table 3.

Table 2. PF-PIS

C_1	C_2	C_3	C_4
0.6,0.5,0.3	0.7,0.5,0.3	0.5,0.6,0.3	0.6,0.5,0.2

and

Table 3. PF-NIS

C_1	C_2	C_3	C_4
0.1,0.2,0.1	0.1,0.1,0.1	0.1,0.1,0.1	0.3,0.1,0.1

Step 4. Compute the distance for PIS and NIS by using Definition 2.3. We showed the distance from PIS and NIS in Table 4 and Table 5.

Table 4. Distance for PIS

C_1	C_2	C_3	C_4
0.5	0.6	0.5	0.3
0.6	0.6	0.4	0.6
0.4	0.6	0.7	0.4
0.5	0.7	0.6	0.4

and

Table 5. Distance for NIS

C_1	C_2	C_3	C_4
0.5	0.6	0.6	0.5
0.4	0.6	0.7	0.2
0.6	0.6	0.4	0.4
0.5	0.5	0.5	0.4

Step 5. Determine the closeness coefficient by using Eq.(6), shown in Table 6.

Table 6. Closeness coefficient

0.5	0.5	0.545455	0.625
0.4	0.5	0.636364	0.25
0.6	0.5	0.363636	0.51
0.5	0.4	0.454545	0.5

Step 6. Create the expanded decision matrix through the insertion of C_{ij} by using Eqns. (7)-(9). Represented the extended decision matrix in Table 7.

Table 7. Extended decision matrix

C^-	C_{1j}	C_{2j}	C_{3j}	C_{4j}	C^+
0.4	0.5	0.4	0.6	0.5	0.6
0.416667	0.5	0.5	0.5	0.416667	0.5
0.363636	0.545455	0.636364	0.363636	0.454545	0.636364
0.25	0.625	0.25	0.5	0.5	0.625

Step 7. Transform the extended decision matrix E into its normalized representation by using Eq. (10). The outcome is shown in Table 8.

Table 8. Normalized extended decision matrix

C^-	C_1	C_2	C_3	C_4	C^+
0.66667	0.83333	0.66667	1	0.83333	1
0.83333	1	1	1	0.714286	1
0.571429	0.857143	1	0.571429	1	1
0.4	1	0.4	0.8	0.8	1

Step 8. Build up the final weighted decision matrix by using Eq. (11). The weighted matrix is shown in Table 9.

Table 9. Weighted decision matrix

C^-	C_1	C_2	C_3	C_4	C^+
0.1507	0.1884	0.1507	0.2261	0.1884	0.2261
0.1835	0.2202	0.2202	0.2202	0.1835	0.2202
0.1465	0.2197	0.2564	0.1465	0.1831	0.2564
0.1189	0.2973	0.1189	0.2378	0.2378	0.2973

Step 9. Evaluate the utility degree of alternatives $\mathfrak{U}_i$ by leveraging Eqns. (12)-(13). The outcome is shown in Table 10.

Table 10. Utility degree of alternatives

$\mathfrak{U}^-$	$\mathfrak{U}^+$
1.5436	0.9257
1.2444	0.7463
1.3852	0.8307
1.3222	0.7929

Step 10. Derive the utility function of alternatives, denoted as $F(\mathfrak{U}_i)$, utilizing Eqns. (14)-(16). The outcome is shown in Table 11.

Table 11. Utility function

$F(\mathfrak{U}_i)$
0.7558
0.6093
0.6782
0.6474

Step 11. Ranking the alternatives is carried out by assessing and organizing them in order of their utility function values. The ranking result is shown in Table 12 and Figure 2.

Table 12. Ranking result

Ranking
$\mathfrak{D}_1 > \mathfrak{D}_3 > \mathfrak{D}_4 > \mathfrak{D}_2$

5 Conclusion

This research study has made a groundbreaking contribution to the field by suggesting the incorporation of the Marcos Method with PFS. The combination of these techniques offers a strong and subtle foundation for decision-making in intricate settings. The efficacy of multi-attribute decision-making has been enhanced by integrating the precision of the Marcos Method with the capability of PFS to manage uncertainties. An application of the Marcos

Method on PFS has been showcased through a case study in the field of sustainable urban development. This innovative technique has been extremely beneficial in dealing with the complexities of decision-making, providing a more thorough and flexible answer. The study demonstrated how this integrated approach improves our capacity to examine and rank alternatives, especially in the realm of urban planning, where uncertainties and dynamic elements are widespread. This research sets the stage for further investigation and implementation of the Marcos Method on PFS in other fields. The findings obtained from this work not only enhance the theoretical underpinnings of decision science but also provide practical applications for tackling real-world problems. This work promotes the ongoing investigation of novel approaches for decision-making in intricate systems, facilitating progress that can have a beneficial influence on a diverse range of disciplines.

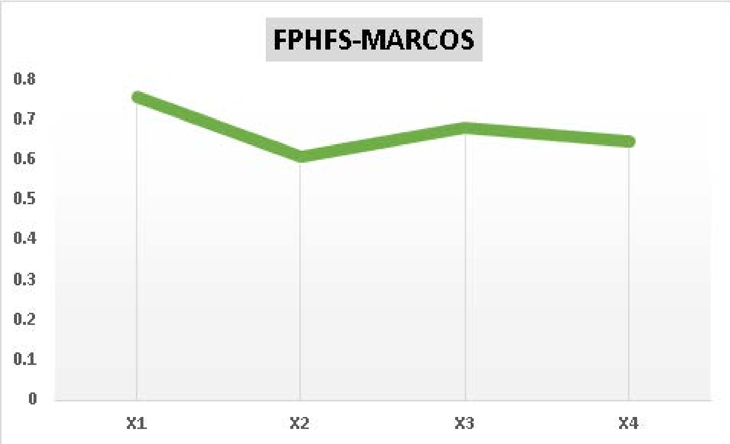

Figure 2. Graphical representation of comparison between the ranking of PLTD and MARCOS method

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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