Selecting the Low-Carbon Tourism Destination: Based on Pythagorean Fuzzy Taxonomy Method

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Abstract: Low-carbon tourism plays the increasingly significant role in carbon emission reduction and natural environmental protection. The choice of low-carbon tourist destination (LCTD) often involves the multiple attributes or criteria and can be regarded as the corresponding multiple attribute group decision making (MAGDM) issues. Since the Pythagorean fuzzy sets (PFSs) could well depict uncertain information or fuzzy information and cope with the LCTD selection, thus this essay develops a framework to tackle such MAGDM issues under the Pythagorean fuzzy environment. In this essay, due to few methods can compare with different alternatives along with their advantages from designed attributes, therefore, to overcome this challenge, the taxonomy method is utilized to integrate with PFSs. What's more, the entropy method is also utilized to determine the attribute weights. Eventually, an application related to LCTD selection and some comparative analysis have been given to demonstrate the superiority of the designed method. The results illustrate that the designed framework is useful for identifying optimal tourist destination among the potential tourist destinations.

Keywords: multiple attribute group decision making (MAGDM); Pythagorean fuzzy sets (PFSs); information entropy; Taxonomy method; low-carbon tourist destination selection

1. Introduction

Since global warming is becoming increasingly serious, the deterioration of the ecological environment has been viewed as a major dilemma for human development. In this context, the concept of ecological civilization has emerged and prospered. As an important part of economic development, the tourism industry is related to the construction of the economic level. By developing the low-carbon tourist destinations (LCTDs), the sustainable development of the tourism industry can be realized and the tourism resources can also be effectively protected. In addition, increasingly, tourists are focusing on environmental friendly and willing to choose a LCTD to relieve their stress. Hence, choosing optimal a LCTD depending on various attributes like carbon reduction, lower energy consumption and environmental protection is crucial for tourists who want to have an enjoyable travel experience. For tourists and others involved, it is a great challenge for them to select the optimal LCTD. To overcome it, a novel multiple attribute group decision making (MAGDM) method is designed to tackle this issue.

In 1763, the taxonomy method was firstly presented by Adanson and then extended by a set of Polish mathematicians in 1950. In 1968, this method was developed as a tool to classify and determine

the development degree by Hellwig [1] to tackle the MAGDM issues. Compared with other MAGDM methods, the merit of this method is that it is really appropriate to grade, classify, and compare various activities with respect to their advantages and utility degree from studied attributes. However, the taxonomy method is only extended to Pythagorean 2-Tuple Linguistic [2], there exists a research gap in constructing the Pythagorean fuzzy taxonomy method. Thus, a novel PF-taxonomy method is designed in this essay and applied to tackle the issue of LCTD selection.

Our contributions of this essay are summarized as follows: (1) an assessment system for the LCTD is developed. This system can help tourists and others involved choose the optimal tourist destination in a scientific and efficient way; (2) the classical taxonomy method is extended to the PF-taxonomy method which means the taxonomy method can be employed to the Pythagorean fuzzy environment; (3) an objective weight determining method is presented to calculate the attributes with different weights.

In a word, regarding to the above analysis, a novel PF-taxonomy method presented in this essay can be believed that it is able to solve the issue of LCTD selection. This novel method adopts the PFSs to express the fuzzy information. Compared with other generalizations of fuzzy sets, Pythagorean fuzzy sets (PFSs) can provide more autonomy to decision makers in articulating their ideas about the vagueness and uncertainty of the considered MAGDM issues. Besides, decision makers cannot be restricted by the condition that the sum of membership and non-membership degrees cannot exceed one. Thus, PFSs are appropriate to applied to the LCTD selection. From the theoretical perspective, the designed method can substantially enhance the theoretical framework of PFSs and also promote their widespread applications in various fields. Altogether, we believe that the novel PF-taxonomy method can offer a scientific and reliable means for making convincing ranking results.

The reminder of our essay proceeds as follows. Related literature review is conducted in Section 2. Some necessary knowledge about PFSs is concisely reviewed in Section 3. The conventional taxonomy method is integrated with PFSs and the calculating procedures are simply depicted in Section 4. An empirical application of LCTDs selection and some comparative analysis are conducted to show the superiority of this approach in Section 5. At last, we make an overall conclusion of our work in Section 6.

2. Literature Review

In numerous decision-making problems, information is regularly depicted through crisp numbers. But in the process of making decision, there exist some situations with fuzzy and uncertainty [3–6]. Hence, it is difficult for DMs(decision makers) to depict their preferences information through an exact numerical value [7–9], which may influence the evaluation results. In order to tackle this issue, Atanassov [10] gave the definition about intuitionistic fuzzy sets (IFSs) which can be utilized to express the vagueness of an event or object numerically. Burillo and Bustince [11] exposed two construction theorems of IFSs from one fuzzy set [12] and a theorem which allowed us to build an IFSs from two fuzzy sets. Hadjitodorov [13] proposed the nearest prototype algorithms along with IFSs. Hung [14] gave the partial correlation of IFSs with multivariate correlation. Hung and Yang [15] developed the similarity measures between IFSs. Xu and Yager [16] developed several geometric operators for IFSs. Cavallaro, et al. [17] evaluated the technologies of concentrated solar power by employing the intuitionistic fuzzy TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution)(IF-TOPSIS) and entropy weights. Garg [18] defined the algorithms for solving IF-MADM issues which has been designed through different entropies and unknown weights. Wu, et al. [19] designed some dombi heronian mean operators under interval-valued intuitionistic fuzzy sets (IVIFSs). Most recently, the Pythagorean fuzzy set (PFS) [20] has appeared as the effective mean to deal with multiple attribute decision making (MADM) issues. The concept of PFS is a generalization of IFS, which is more useful than the IFS. To be special, PFS can provide more flexibility and power in modeling and expressing the imprecise and imperfect information. Zhang and Xu [21] devised the Pythagorean fuzzy numbers (PFNs) and then defined the PF-TOPSIS for MADM issue. Gou, et al. [22] thought the continuous PFNs' properties. Peng and Yang [23] designed the superiority and inferiority ranking of PFNs to solve MAGDM. Liang,

et al. [24] investigated the Bonferroni mean (BM) and weighted BM (WBM) operator with PFNs. Liang, et al. [25] studied the operators of PFGBM, weighted PFGBM (WPFGBM) in the MCGDM issue. Ren, et al. [26] devised the PF-TODIM (an acronym in Portuguese of interactive and multi-criteria decision making) algorithms which considered DMs' psychological behaviors. Li and Lu [27] defined some new similarity and distance measures for PFSs. Zeb et al. [28] proposed credible extended PFSs (C-EPFSs) and possible extended PFSs (P-EPFSs). Zeng, et al. [29] gave the MAGDM framework under PFSs with self-confidence of DMs. Gul et al. [30] supplied the PF-VIKOR (VIseKriterijumska Optimizacija I KOmpromisno Resenje) approach for potential hazards of risk management. Garg [31] developed some novel logarithm operational laws for the PFSs. Liang, et al. [32] considered the compromised solution's perspective, which can consider the DM's psychological behavior along with the TODIM and VIKOR methods. Thao and Smarandache [33] defined the PFSs' fuzzy entropy. Yu et al. [34] gave the distance operator of IOWA (induced ordered weighted average) in PF-MAGDM. Chen [35] designed the PF-PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) algorithms for MCDA (Multi-criteria decision analysis). Chen [36] defined the consensus sorting method that employed the mixed choice for MCDA under PFSs. Chen [37] defined the PF-VIKOR methods for MADM issues. Chen [38] proposed the correlation-based compromise model for MCDA issues under PFSs. Teng et al. [39] defined the power MSM (Maclaurin Symmetric Mean)operators for Pythagorean fuzzy linguistic setting. Geng et al. [40] defined the Pythagorean fuzzy uncertain linguistic set and developed the TODIM method for MCGDM issues.

3. Preliminaries

The primary theories of PFSs [20] are simply reviewed in such section.

Definition 1. [20] *Let X be a fix set. A PFS is an object having the following form*

$$PFS = \{\langle x, (p\mu(x), pv(x))\rangle | x \in X\} \tag{1}$$

where the mathematical function $p\mu : X \to [0,1]$ depicts the membership degree and the mathematical function $pv : X \to [0,1]$ depicts the non-membership degree of $x \in X$ to PFS, and, for each $x \in X$, it meets that:

$$(p\mu(x))^2 + (pv(x))^2 \le 1 \tag{2}$$

Definition 2. [41] *Let $pa = (p\mu, pv)$ be the PFN, a PFN's score value SV can be designed in the following:*

$$SV(pa) = \frac{1}{2}\left(1 + p\mu^2 - pv^2\right), \ SV(pa) \in [0,1]. \tag{3}$$

Definition 3. [21] *Let $pa = (p\mu, pv)$ be the PFN, a PFN's accuracy value HV can be designed in the following:*

$$HV(pa) = p\mu^2 + pv^2, HV(pa) \in [0,1] \tag{4}$$

to assess the accuracy degree in the PFN $pa = (p\mu, pv)$, where $HV(pa) \in [0,1]$. The higher the value of $HV(pa) \in [0,1]$ is, the more the accuracy degree of $pa = (p\mu, pv)$.

In the following, Zhang and Xu [21] designed a relationship of ranking between two PFNs.

Definition 4. [21] *Let $pa_1 = (p\mu_1, pv_1)$ and $pa_2 = (p\mu_2, pv_2)$ be two PFNs, $SV(pa_1) = \frac{1}{2}\left(1 + p\mu_1{}^2 - pv_1{}^2\right)$ and $SV(pa_2) = \frac{1}{2}\left(1 + p\mu_2{}^2 - pv_2{}^2\right)$ be the scores of pa_1 and pa_2, and let $HV(pa_1) = p\mu_1{}^2 + pv_1{}^2$ and $HV(pa_2) = p\mu_2{}^2 + pv_2{}^2$ be the accuracy degrees of $pa_1 = (p\mu_1, pv_1)$ and $pa_2 = (p\mu_2, pv_2)$.*
If $SV(pa_1) < SV(pa_2)$, then $pa_1 < pa_2$;

and if $SV(pa_1) = SV(pa_2)$, then

a. *if $HV(pa_1) = HV(pa_2)$, then $pa_1 = pa_2$;*
b. *if $HV(pa_1) < HV(pa_2)$, then, $pa_1 < pa_2$.*

Example 1. *Suppose that $pa_1 = (0.4, 0.4)$ and $pa_2 = (0.6, 0.6)$ be two PFNs. Then, the ranking order between pa_1 and pa_2 should be $pa_1 < pa_2$ due to the fact that from Definition 4 we can see that if $SV(pa_1) = SV(pa_2)$ but $HV(pa_1) < HV(pa_2)$, then $pa_1 < pa_2$.*

Definition 5. [21] *Let $pa_1 = (p\mu_1, pv_1)$, $pa_2 = (p\mu_2, pv_2)$, and $pa = (p\mu, pv)$ be three PFNs, and their main operations are designed in the following:*

① $pa_1 \oplus pa_2 = \left(\sqrt{(p\mu_1)^2 + (p\mu_2)^2 - (p\mu_1)^2 (p\mu_2)^2}, pv_1 pv_2 \right)$;

② $pa_1 \otimes pa_2 = \left(p\mu_1 p\mu_2, \sqrt{(pv_1)^2 + (pv_2)^2 - (pv_1)^2 (pv_2)^2} \right)$;

③ $\lambda pa = \left(\sqrt{1 - (1 - p\mu^2)^\lambda}, pv^\lambda \right), \lambda > 0$;

④ $(pa)^\lambda = \left(p\mu^\lambda, \sqrt{1 - (1 - pv^2)^\lambda} \right), \lambda > 0$;

⑤ $pa^c = (pv, p\mu)$.

Definition 6. [21] *Let $pa_1 = (p\mu_1, pv_1)$ and $pa_2 = (p\mu_2, pv_2)$ be two PFNs, then the normalized Hamming distance of $pa_1 = (p\mu_1, pv_1)$ and $pa_2 = (p\mu_2, pv_2)$ is designed:*

$$d(pa_1, pa_2) = \frac{1}{2} \left(\left| (p\mu_1)^2 - (p\mu_2)^2 \right| + \left| (pv_1)^2 - (pv_2)^2 \right| \right) \tag{5}$$

4. Taxonomy Method for Pythagorean Fuzzy MAGDM Issues with Entropy Weight

In this chapter, the Pythagorean fuzzy taxonomy (PF-taxonomy) method is presented for MAGDM issues with unknown weight. The subsequently notations are utilized to depict the PF-MAGDM issues. Let $F = \{F_1, F_2, \ldots, F_m\}$ be a collection possible alternatives, and the chosen attributes set $T = \{T_1, T_2, \ldots, T_n\}$ with weight vector $w = (w_1, w_2, \ldots, w_n)$, where $w_j \in [0, 1]$, $\sum_{j=1}^{n} w_j = 1$ and a collection of experts $E = \{E_1, E_2, \ldots, E_q\}$ with weight vector $\phi = (\phi_1, \phi_2, \ldots, \phi_q)$, where $\phi_k \in [0, 1]$, $\sum_{k=1}^{q} \phi_k = 1$. Assume that there are m attributes for $F = \{F_1, F_2, \ldots, F_m\}$ and their values are assessed by q qualified experts and represented as PFN matrix $PR^{(k)} = \left(pr_{ij}^{(k)} \right)_{m \times n}$, $pr_{ij}^{(k)} = \left(p\mu_{ij}^{(k)}, pv_{ij}^{(k)} \right)_{m \times n}$, $i = 1, 2, \ldots, m, j = 1, 2, \ldots, n, k = 1, 2, \ldots, q$.

After that, the PF-taxonomy method is employed to address PF-MAGDM issues with entropy weight. The detailed computing procedures are shown in the following flowchart (See Figure 1):
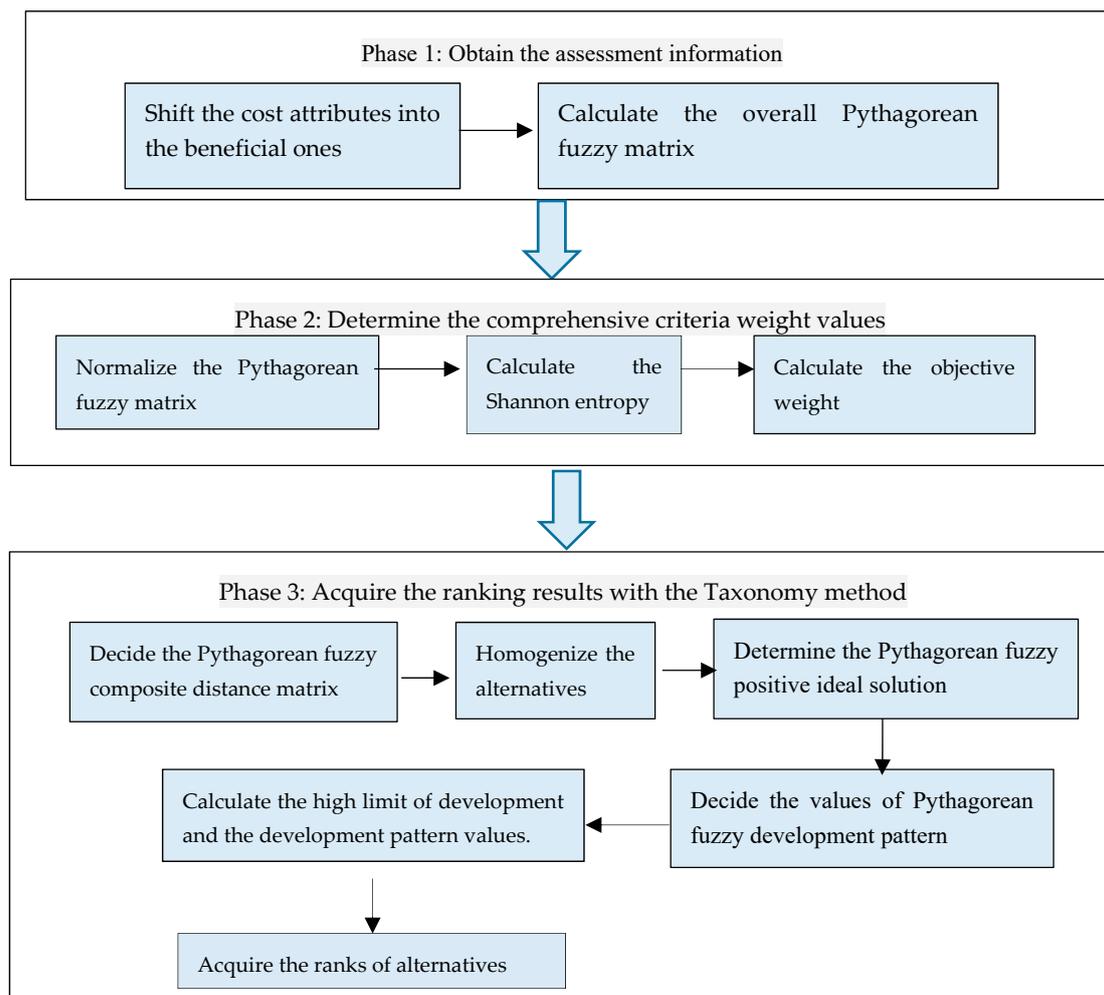
Figure 1. The structure of the presented method.

(I)   Phase 1: Obtain the assessment information

Step 1.   The cost attribute is shifted into the beneficial attribute. If the cost value is $\left(p\mu_{ij}^{(k)}, pv_{ij}^{(k)}\right)$, then the corresponding beneficial value is $\left(pv_{ij}^{(k)}, p\mu_{ij}^{(k)}\right)$.

Step 2.   Calculate the Pythagorean fuzzy overall matrix $PR^{(k)} = \left(pr_{ij}^{(k)}\right)_{m \times n}$, $pr_{ij}^{(k)} = \left(p\mu_{ij}^{(k)}, pv_{ij}^{(k)}\right)_{m \times n}$ $i = 1, 2, \ldots, m, j = 1, 2, \ldots, n, k = 1, 2, \ldots, q$ by taking advantage of PFWA (Pythagorean fuzzy weighted average) operator and $PFA_i = (PFA_{i1}, PFA_{i2}, \ldots, PFA_{in})$, $PFA_{ij} = \left(p\mu_{ij}, pv_{ij}\right)$.

$$pr_{ij} = \left(p\mu_{ij}, pv_{ij}\right) = \text{PFWA}_\phi\left(pr_{ij}^{(1)}, pr_{ij}^{(2)}, \ldots, pr_{ij}^{(q)}\right) = \bigoplus_{k=1}^{q}\left(\phi_k pr_{ij}^{(k)}\right)$$
$$= \left(\sqrt{1 - \prod_{k=1}^{q}\left(1 - \left(p\mu_{ij}^{(k)}\right)^2\right)^{\phi_k}}, \prod_{k=1}^{q}\left(pv_{ij}^{(k)}\right)^{\phi_k}\right) \tag{6}$$

(II)   **Phase 2:** Determine the comprehensive criteria weight values

Step 3.   Utilize the entropy to calculate the weight.

The attributes' weight is of vital significant to MAGDM issues. Numerous researchers have paid attention to MAGDM issues with incomplete weight information. Entropy [42] is viewed as a classical term in the information theory which is also employed to derive attributes' weight. The greater the degree of dispersion, the greater the degree of differentiation and more information can be derived. Compared with various subjective weighting methods, the superiority of the entropy method is to avoid human factors' interference on the weight of indicators, thus enhancing the objectivity of the comprehensive evaluation results. Firstly, the normalized Pythagorean fuzzy matrix $NPF_{ij}(p)$ is determined:

$$NPF\big(SV\big(pr_{ij}\big)\big) = \frac{SV\big(pr_{ij}\big)}{\sum\limits_{i=1}^{m} SV\big(pr_{ij}\big)}, \ j = 1, 2, \ldots, n, \tag{7}$$

Then, the corresponding information of Shannon entropy $E = (E_1, E_2, \ldots, E_n)$ is derived by using Equation (8):

$$E_j = -\frac{1}{\ln m} \sum_{i=1}^{m} NPF\big(SV\big(pr_{ij}\big)\big) \ln NPF\big(SV\big(pr_{ij}\big)\big) \tag{8}$$

and $NPF\big(SV\big(pr_{ij}\big)\big) \ln NPF\big(SV\big(pr_{ij}\big)\big)$ is designed as 0, if $NPF\big(SV\big(pr_{ij}\big)\big) = 0$.

In the end, the attribute weights $w = (w_1, w_2, \ldots, w_n)$ is derived:

$$w_j = \frac{1 - E_j}{\sum\limits_{j=1}^{n} \big(1 - E_j\big)}, \ j = 1, 2, \ldots, n. \tag{9}$$

(III) **Phase 3:** Acquire the ranking results with the taxonomy method

Step 4. Calculate the Pythagorean fuzzy composite distance matrix (*PFCDM*):

Above all, each alternative's distance from the other alternatives compared to every attribute is derived by utilizing Equation (10):

$$PFCDM_{ik} = w_j \sum_{j=1}^{n} \big(d\big(\big(p\mu_{ij}, pv_{ij}\big), \big(p\mu_{kj}, pv_{kj}\big)\big)\big) \tag{10}$$

Then, the *PFCDM* between alternatives is depicted as Equation (11).

$$PFCDM = \begin{bmatrix} PFCDM_{11} & PFCDM_{12} & \ldots & PFCDM_{1m} \\ PFCDM_{21} & PFCDM_{22} & \ldots & PFCDM_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ PFCDM_{m1} & PFCDM_{m2} & \ldots & PFCDM_{mm} \end{bmatrix} \tag{11}$$

Step 5. The alternatives are homogenized.

Firstly, each row's minimum distance value is derived between alternatives in the *PFCDM*. Following this, for each row, the minimum distance values' the mean and standard deviation are obtained in the light of Equation (12), respectively.

$$\overline{PFO} = \frac{1}{m} \sum_{i=1}^{m} PFO_i, \ S_{PFO} = \sqrt{\frac{1}{m} \sum_{i=1}^{m} \big(PFO_i - \overline{PFO}\big)^2} \tag{12}$$

where PFO_i is the *ith* row's minimum distance in *PFCDM*.

Subsequently, the homogeneity range of *PFCDM* can be derived by Equation (13).

$$PFO = \overline{PFO} \pm 2S_{PFO} \tag{13}$$

If each row's minimum distance values do not belong to the interval Equation (13), the corresponding alternatives are inhomogeneous and should be deleted, and then the mean and standard deviation should be calculated again.

Step 6. Define the Pythagorean fuzzy positive ideal solution (*PFPIS*):

$$PFPIS = (PFPIS_1, PFPIS_2, \dots, PFPIS_n) \tag{14}$$

where

$$PFPIS_j = \left(\max_i p\mu_{ij}, \min_i pv_{ij} \right) = \left(p\mu_j^+, pv_j^+ \right) \tag{15}$$

Step 7. Calculate the Pythagorean fuzzy development pattern for each alternative:

After the alternatives are homogenized, the attribute development pattern is calculated by Equations (16) and (17) utilizing the Pythagorean fuzzy overall decision matrix $PR = \left(pr_{ij} \right)_{m \times n}, pr_{ij} = \left(p\mu_{ij}, pv_{ij} \right)_{m \times n}$ $(i = 1, 2, \dots, m, j = 1, 2, \dots, n)$ obtained in the second step.

$$PFDP(PFA_i, PFPIS) = \sum_{j=1}^{n} w_j \left(d \left(PFA_{ij}, PFPIS_j \right) \right) \tag{16}$$

$$d \left(PFA_{ij}, PFPIS_j \right) = \frac{1}{2} \left(\left| \left(p\mu_{ij} \right)^2 - \left(p\mu_j^+ \right)^2 \right| + \left| \left(pv_{ij} \right)^2 - \left(pv_j^+ \right)^2 \right| \right) \tag{17}$$

where $PFDP(PFA_i, PFPIS)$ illustrates the Pythagorean fuzzy development pattern for *ith* alternative.

Step 8. Calculate the Pythagorean fuzzy high limit of development ($PFHLD_0$) and the Pythagorean fuzzy development pattern values ($PFDPV_i (i = 1, 2, \dots, m)$) as follows:

At this step, the $PFHLD_0$ is firstly calculated according to Equations (18)–(20):

$$PFHLD_0 = \overline{PFDP(PFA_i, PFPIS)} + 2S_{PFDP(PFA_i, PFPIS)} \tag{18}$$

$$\overline{PFDP(PFA_i, PFPIS)} = \frac{1}{m} \sum_{i=1}^{m} PFDP(PFA_i, PFPIS) \tag{19}$$

$$S_{PFDP(PFA_i, PFPIS)} = \sqrt{\frac{1}{m} \sum_{i=1}^{m} \left(PFDP(PFA_i, PFPIS) - \overline{PFDP(PFA_i, PFPIS)} \right)^2} \tag{20}$$

Subsequently, the alternatives are ranked by $PFDPV_i (i = 1, 2, \dots, m)$ which can be got from Equation (21).

$$PFDPV_i = \frac{PFDP(PFA_i, PFPIS)}{PFHLD_0}, \ i = 1, 2, \dots, m. \tag{21}$$

Step 9. Depending on the $PFDPV_i (i = 1, 2, \dots, m)$, all alternatives' order can be derived. The amount of $PFDPV_i (i = 1, 2, \dots, m)$ ranges from zero to one, and any value closed to zero means the alternative with greater development (the highest rank) and any value closed to one indicates that the alternative lacks development (the lowest rank). Therefore, the alternative with the smallest $PFDPV_i (i = 1, 2, \dots, m)$ value is the optimal.

5. The Numerical Example and Comparative Analysis

5.1. The Numerical Example

With the speedy development of economic, energy consumption in all walks of life has risen sharply and carbon emissions have dramatic increased, which has made China become one of the largest carbon-emitting countries in all over the world. According to the statistics, compared with 2016, global carbon emissions in 2017 increased by 2%, about 37 billion tons. This growth broke the situation of maintaining zero growth in the past three years. And, the total carbon emissions in China are about 10.3 billion tons, accounting for 28% of the global carbon emissions. Thus, the carbon emission reduction pressure in China is huge. Unlike developed countries that have entered the post-industrial era, China is in a stage of rapid industrialization. The growing demand for resources is the direct cause of the increase in carbon emissions. In this context, developing a low-carbon economy is an effective way to coordinate the economic development and carbon reduction in China [43–46]. Since people's demand for tourism and leisure is increasing, tourism has become an important part of Chinese economy. From the environmental characteristics of tourism, tourism is a relatively high level of carbon emission industry [47,48]. According to the characteristics of current tourism activities and the increasing speed of tourism demand, and in accordance with the current mode of development, although tourism is beneficial to the national economy, it does not contribute to the coordinated development of economic environment, but also has the opposite effect. Therefore, tourism should play a greater role in the coordinated development of China's economy and environment, and low-carbon development is the inevitable choice of tourism. In the tourism industry, transportation, accommodation and tourism activities are the main sources of carbon emissions. Therefore, tourists continue to generate carbon emissions during the travel process. It is estimated that the total carbon emissions generated by Chinese tourism industry will be nearly 157 million tons in 2017. Among them, tourism and transportation are the parts with the largest carbon emissions in the tourism industry. Their carbon emissions are about 140 million, accounting for 92% of the total [49–51]. Therefore, the visited tourists play an important role in the carbon emission reduction for the tourism industries. In order to reduce the carbon emission of the tourism industry, it is necessary to have a deep understanding of the influencing factors and mechanism of tourists' low-carbon tourism behavior. The low-carbon tourist destination selection issue is a conventional MAGDM issue [52–58]. Therefore, it is especially important to make reasonable decisions in the actual promotion and construction of low-carbon tourism. Low-carbon tourist destination selection, low-carbon tourist destination demonstration area construction and low-carbon supplier selection generally involve many decision makers evaluating alternatives, so it has theoretical and practical significance to investigate the application of MAGDM methods in the low-carbon tourism. Thus, in such part, a numerical example related to LCTD selection is provided to demonstrate the superiority of the developed method.

There is a panel with five possible low-carbon tourist destination spots $F_i(i = 1, 2, 3, 4, 5)$ to select. There are four selected attributes for invited experts to assess the five potential LCTD spots: ①T_1 is attraction and impact of tourist destination spots; ②T_2 is transportation cost of tourist destination spots; ③T_3 is hotels and accommodation of tourist destination spots; ④T_4 is consumption satisfaction of tourist destination spots. The transportation cost (T_2) is cost attribute, others are beneficial attributes. The five potential LCTD spots $F_i(i = 1, 2, 3, 4, 5)$ are to be assessed through PFNs by five DMs under four attributes, as recorded in the Tables 1–5.

Table 1. Pythagorean fuzzy matrix by DM (decision maker)$_1$.

Alternatives	T_1	T_2	T_3	T_4
F_1	(0.40, 0.70)	(0.40, 0.50)	(0.30, 0.80)	(0.50, 0.70)
F_2	(0.60, 0.70)	(0.40, 0.60)	(0.50, 0.80)	(0.30, 0.90)
F_3	(0.50, 0.70)	(0.50, 0.60)	(0.40, 0.80)	(0.50, 0.80)
F_4	(0.40, 0.80)	(0.40, 0.80)	(0.50, 0.70)	(0.60, 0.80)
F_5	(0.60, 0.80)	(0.50, 0.70)	(0.60, 0.80)	(0.50, 0.70)

Table 2. Pythagorean fuzzy matrix by DM$_2$.

Alternatives	T_1	T_2	T_3	T_4
F_1	(0.50, 0.80)	(0.60, 0.30)	(0.30, 0.60)	(0.50, 0.70)
F_2	(0.70, 0.50)	(0.70, 0.20)	(0.70, 0.20)	(0.40, 0.50)
F_3	(0.60, 0.40)	(0.50, 0.70)	(0.50, 0.30)	(0.60, 0.30)
F_4	(0.80, 0.10)	(0.60, 0.30)	(0.30, 0.40)	(0.50, 0.60)
F_5	(0.60, 0.40)	(0.40, 0.80)	(0.70, 0.60)	(0.50, 0.80)

Table 3. Pythagorean fuzzy matrix by DM$_3$.

Alternatives	T_1	T_2	T_3	T_4
F_1	(0.30, 0.60)	(0.20, 0.80)	(0.10, 0.60)	(0.30, 0.50)
F_2	(0.50, 0.60)	(0.20, 0.80)	(0.40, 0.70)	(0.30, 0.90)
F_3	(0.30, 0.50)	(0.30, 0.40)	(0.20, 0.80)	(0.50, 0.70)
F_4	(0.20, 0.60)	(0.20, 0.70)	(0.30, 0.50)	(0.40, 0.60)
F_5	(0.50, 0.60)	(0.40, 0.70)	(0.40, 0.70)	(0.30, 0.50)

Table 4. Pythagorean fuzzy matrix by DM$_4$.

Alternatives	T_1	T_2	T_3	T_4
F_1	(0.40, 0.60)	(0.30, 0.50)	(0.20, 0.30)	(0.40, 0.20)
F_2	(0.60, 0.30)	(0.30, 0.50)	(0.50, 0.40)	(0.40, 0.60)
F_3	(0.40, 0.20)	(0.40, 0.80)	(0.30, 0.50)	(0.60, 0.40)
F_4	(0.20, 0.30)	(0.30, 0.70)	(0.40, 0.70)	(0.50, 0.30)
F_5	(0.60, 0.30)	(0.50, 0.60)	(0.50, 0.40)	(0.40, 0.20)

Table 5. Pythagorean fuzzy matrix by DM$_5$.

Alternatives	T_1	T_2	T_3	T_4
F_1	(0.80, 0.50)	(0.50, 0.70)	(0.70, 0.60)	(0.60, 0.80)
F_2	(0.60, 0.40)	(0.60, 0.50)	(0.50, 0.70)	(0.80, 0.60)
F_3	(0.40, 0.50)	(0.50, 0.70)	(0.60, 0.70)	(0.70, 0.50)
F_4	(0.80, 0.50)	(0.30, 0.80)	(0.70, 0.60)	(0.60, 0.40)
F_5	(0.20, 0.20)	(0.20, 0.20)	(0.20, 0.20)	(0.20, 0.20)

Besides, the PF-taxonomy method is utilized to select the optimal low-carbon tourist destination spots.

Step 1. Cost attribute T_2 is shifted into beneficial attribute (See Tables 6–10).

Table 6. Pythagorean fuzzy matrix by DM_1.

Alternatives	T_1	T_2	T_3	T_4
F_1	(0.40, 0.70)	(0.50, 0.40)	(0.30, 0.80)	(0.50, 0.70)
F_2	(0.60, 0.70)	(0.60, 0.40)	(0.50, 0.80)	(0.30, 0.90)
F_3	(0.50, 0.70)	(0.60, 0.50)	(0.40, 0.80)	(0.50, 0.80)
F_4	(0.40, 0.80)	(0.80, 0.40)	(0.50, 0.70)	(0.60, 0.80)
F_5	(0.60, 0.80)	(0.70, 0.50)	(0.60, 0.80)	(0.50, 0.70)

Table 7. Pythagorean fuzzy matrix by DM_2.

Alternatives	T_1	T_2	T_3	T_4
F_1	(0.50, 0.80)	(0.30, 0.60)	(0.30, 0.60)	(0.50, 0.70)
F_2	(0.70, 0.50)	(0.20, 0.70)	(0.70, 0.20)	(0.40, 0.50)
F_3	(0.60, 0.40)	(0.70, 0.50)	(0.50, 0.30)	(0.60, 0.30)
F_4	(0.80, 0.10)	(0.30, 0.60)	(0.30, 0.40)	(0.50, 0.60)
F_5	(0.60, 0.40)	(0.80, 0.40)	(0.70, 0.60)	(0.50, 0.80)

Table 8. Pythagorean fuzzy matrix by DM_3.

Alternatives	T_1	T_2	T_3	T_4
F_1	(0.30, 0.60)	(0.80, 0.20)	(0.10, 0.60)	(0.30, 0.50)
F_2	(0.50, 0.60)	(0.80, 0.20)	(0.40, 0.70)	(0.30, 0.90)
F_3	(0.30, 0.50)	(0.40, 0.30)	(0.20, 0.80)	(0.50, 0.70)
F_4	(0.20, 0.60)	(0.70, 0.20)	(0.30,0.50)	(0.40, 0.60)
F_5	(0.50, 0.60)	(0.70, 0.40)	(0.40, 0.70)	(0.30, 0.50)

Table 9. Pythagorean fuzzy matrix by DM_4.

Alternatives	T_1	T_2	T_3	T_4
F_1	(0.40, 0.60)	(0.50, 0.30)	(0.20, 0.30)	(0.40, 0.20)
F_2	(0.60, 0.30)	(0.50, 0.30)	(0.50, 0.40)	(0.40, 0.60)
F_3	(0.40, 0.20)	(0.80, 0.40)	(0.30, 0.50)	(0.60, 0.40)
F_4	(0.20, 0.30)	(0.70, 0.30)	(0.40, 0.70)	(0.50, 0.30)
F_5	(0.60, 0.30)	(0.60, 0.50)	(0.50, 0.40)	(0.40, 0.20)

Table 10. Pythagorean fuzzy matrix by DM_5.

Alternatives	T_1	T_2	T_3	T_4
F_1	(0.80, 0.50)	(0.70, 0.50)	(0.70, 0.60)	(0.60, 0.80)
F_2	(0.60, 0.40)	(0.50, 0.60)	(0.50, 0.70)	(0.80, 0.60)
F_3	(0.40, 0.50)	(0.70, 0.50)	(0.60, 0.70)	(0.70, 0.50)
F_4	(0.80, 0.50)	(0.80, 0.30)	(0.70, 0.60)	(0.60, 0.40)
F_5	(0.20, 0.20)	(0.20, 0.20)	(0.20, 0.20)	(0.20, 0.20)

Step 2.　Calculate the Pythagorean fuzzy overall decision matrix (Table 11) by Equation (6).

Table 11. Pythagorean fuzzy overall assessing matrix.

Alternatives	T_1	T_2
F_1	(0.5437, 0.6320)	(0.6139, 0.3728)
F_2	(0.6072, 0.4789)	(0.5838, 0.3987)
F_3	(0.4580, 0.4258)	(0.6708, 0.4317)
F_4	(0.6071, 0.3728)	(0.7084, 0.3366)
F_5	(0.5325, 0.4095)	(0.6596, 0.3807)
Alternatives	T_3	T_4
F_1	(0.4085, 0.5533)	(0.4769, 0.5232)
F_2	(0.5383, 0.5004)	(0.5176, 0.6804)
F_3	(0.4340, 0.5827)	(0.5902, 0.5073)
F_4	(0.4823, 0.5674)	(0.5291, 0.5102)
F_5	(0.5264, 0.4852)	(0.4027, 0.4027)

Step 3. Derive the attributes' weight through Equations (7)–(9): $w_1 = 0.2522, w_2 = 0.2674, w_3 = 0.2386, w_4 = 0.2418$.

Step 4. Calculate the Pythagorean fuzzy composite distance matrix (Table 12) by Equations (10) and (11):

Table 12. Pythagorean fuzzy composite distance matrix.

	F_1	F_2	F_3	F_4	F_5
F_1	-	0.0872	0.0776	0.0799	0.0818
F_2	0.0872	-	0.1017	0.0804	0.0850
F_3	0.0776	0.1017	-	0.0581	0.0751
F_4	0.0799	0.0804	0.0581	-	0.0688
F_5	0.0818	0.0850	0.0751	0.0688	-

Step 5. Homogenize the alternatives.

Above all, depending on the calculating results of the PFCDM (Table 12), each row's Pythagorean fuzzy shortest distance is derived as follows:

$$PFO_1 = 0.0776, PFO_2 = 0.0804, PFO_3 = 0.0581$$
$$PFO_4 = 0.0581, PFO_5 = 0.0688$$

In addition, in the composite distance matrix, the values of homogeneity range can be determined by deriving the mean and standard deviation of the Pythagorean fuzzy shortest distance values of each row, which are using the Equations (12) and (13):

$$\overline{PFO} = 0.0686, S_{PFO} = 0.0094$$

$$PFO = \overline{PFO} \pm 2S_{PFO} = 0.0686 \pm 2 * 0.0094 = 0.0686 \pm 0.0188$$

Therefore, in PFCDM, all the Pythagorean fuzzy shortest distance values of each row are within this range, and the corresponding alternatives are homogeneous.

Step 6. Obtain the Pythagorean fuzzy positive ideal solution (*PFPIS*) by Equations (14) and (15) (Table 13):

Table 13. Pythagorean fuzzy positive ideal solution (PFPIS).

	T_1	T_2
PFPIS	(0.6072, 0.3728)	(0.7084, 0.3366)
	T_3	T_4
PFPIS	(0.5383, 0.4852)	(0.5902, 0.4072)

Step 7. Calculate the Pythagorean fuzzy development pattern for each alternative by Equations (16) and (17):

$$PFDP(PFA_1, PFPIS) = 0.1130, PFDP(PFA_2, PFPIS) = 0.0865$$
$$PFDP(PFA_3, PFPIS) = 0.0777, PFDP(PFA_4, PFPIS) = 0.0368$$
$$PFDP(PFA_5, PFPIS) = 0.0515$$

Step 8. Calculate the Pythagorean fuzzy high limit of development $PFHLD_0$ and the Pythagorean fuzzy development pattern values $PFDPV_i (i = 1, 2, 3, 4, 5)$ as follows.

Firstly, the Pythagorean fuzzy high limit of development $PFHLD_0$ can be calculated by Equations (18)–(20):

$$PFHLD_0 = 0.1265$$

In addition, the Pythagorean fuzzy development pattern values $PFDPV_i (i = 1, 2, 3, 4, 5)$ can be obtained by Equation (21):

$$PFDPV_1 = 0.8927, PFDPV_2 = 0.6834, PFDPV_3 = 0.6140,$$

$$PFDPV_4 = 0.2911, \ PFDPV_5 = 0.4073$$

Step 9. According to the $PFDPV_i (i = 1, 2, 3, 4, 5)$, all the low-carbon tourist destination spots can be ranked. Evidently, the rank is $F_4 > F_5 > F_3 > F_2 > F_1$ and the optimal low-carbon tourist destination spot is F_4.

5.2. Comparative Analysis

In this chapter, our developed approach is compared with the operators of PFWA and PFWG (Pythagorean fuzzy weighted geometric) [59], the operators of SPFWA and SPFWG (symmetric Pythagorean fuzzy weighted averaging) [59], PFWMSM (Pythagorean fuzzy weighted Maclaurin symmetric mean) operator [60], PFIWA (pythagorean fuzzy interaction weighted averaging) operator, PFIWG (pythagorean fuzzy interaction weighted geometric) operator [61]. The alternatives' ranking through these existing methods are listed in Table 14.

Table 14. Alternatives' ranking by some existing methods.

Methods	Order
PFWA operator	$F_4 > F_5 > F_3 > F_2 > F_1$
PFWG operator	$F_4 > F_5 > F_3 > F_2 > F_1$
SPFWA operator	$F_4 > F_5 > F_3 > F_2 > F_1$
SPFWG operator	$F_4 > F_5 > F_3 > F_2 > F_1$
PFWMSM operator	$F_4 > F_5 > F_2 > F_3 > F_1$
PFIWA operator	$F_4 > F_5 > F_3 > F_2 > F_1$
PFIWG operator	$F_4 > F_5 > F_3 > F_2 > F_1$
PF-taxonomy method	$F_4 > F_5 > F_3 > F_2 > F_1$

Comparing the results of the PF-taxonomy method with PFWA, PFWG, SPFWA operator, SPFWG, PFWMSM operator, PFIWA operator and PFIWG operator, for the fused values, there are slightly different in alternatives' order and the best alternative and the worst alternative are same.

The above mentioned operators have their own advantages. Specifically, SPFWA and SPFWG operators introduce the neutrality operations and scalar neutrality operations on PFNs, which takes the attitude of the decision makers into consideration. PFWMSM operator captures the interrelationship among the multi input arguments and has a desirable property that monotonically decreasing with respect to the parameter k, which provides the decision makers to choose the appropriate value in accordance with their risk preferences. PFIWA and PFIWG operators can more accurately model the interaction relationships between attributes by introducing the interaction structure. But all the mentioned operators have lower differentiation degrees for all alternatives' final results, which are difficult for DMs to choose the optimal alternative in convincing way. Although the calculating procedures of PF-taxonomy method are more complex than above operators, it cannot be viewed as its weak point. In opposite, the designed method in this essay has a high degree of differentiation. Since it grades, classifies, and compares various activities with respect to their advantages and utility degree from studied attributes. Thus, its ranking result is more precise.

6. Conclusions

In the trend of global warming, the international community has achieved relevant cooperation frameworks to cope with climate change. China is actively undertaking emission reduction commitments, paying high attention to a low-carbon economy. As a green travel mode along with low energy consumption and low emission pollution, the development mode of low-carbon tourism is the positive response of national carbon reduction strategy, also the essential requirement of heavy reliance on ecological environment. Thus, it is urgent to for government to adopt an effective LCTD selection system. This essay offers an effective solution for this issue, since it integrates taxonomy method with Pythagorean fuzzy information to establish the evaluation system of selecting the optimal LCTD.

In this paper, the taxonomy method is proposed to the PFSs to tackle some MAGDM which have unknown weight information. What's more, the score values is utilized to address the Pythagorean fuzzy entropy, which can be utilized to derive the attribute weights. In addition, the optimal alternative is derived through computing the smallest Pythagorean fuzzy development pattern values from the PFPIS. At last, a LCTD selection case study is offered to verify the effectiveness of the designed MAGDM model and some comparative analysis is employed to proof the applicability in practical MAGDM. In summary, a scientific decision framework for LCTD selection is offered in this essay owing to the subsequently two points: (1) regarding to the inherent uncertainty in the process of selecting LCTD, Pythagorean fuzzy information is applied to tackle it directly. (2) The objective for the weight of criteria is considered. In such research, the developed method is regarded as the useful tool to address uncertain and fuzzy decision-making issues.

However, the main drawback of this essay is that the figure for DMs is small and the interdependency of criteria is not taken into consideration, which may restrict the developed method's applications to some extent. For future research, the amount of DMs and the evaluation criteria should be increased to properly evaluate its accuracy. Further, some methods like the analytic network process (ANP) and the DEMATEL (Decision Making Trial and Evaluation Laboratory) method can be utilized to address the interdependency of criteria. Furthermore, the designed models and methods in such essay could be integrated with other MAGDM methods like the AHP (Analytic Hierarchy Process) method to tackle various practical decision-making issues [62–67] and extended to some other fuzzy environments, such as hesitant fuzzy context and Q-rung orthopair fuzzy context [68–78].

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