Solar Power Plant Location Selection Problem by using ELECTRE-III Method in Pythagorean Neutrosophic Programming Approach (A case study on Green Energy in India)

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Solar Power Plant Location Selection Problem by using ELECTRE-III Method in Pythagorean Neutrosophic Programming Approach

(A case study on Green Energy in India)

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Abstract: India dropped its target of generating 500 GW of renewable energy capacity from non-fossil fuel sources by 2030. Its responsibilities to the United Nations Framework Convention on Climate Change [UNFCCC],and reducing carbon radiations by one billion tonnes by the end of the decade at the COP26 conference, held in Glasgow in November 2022.Researchers are continually searching for inexhaustible and reasonable energy sources. Solar energy is one of the greenest sources of energy and is also one of the cleanest. The most important factor in using solar energy is the location of the solar power plant. The main objective of this study is to find the best location for a new solar power plant in a specific region called Bundelkhand region of Uttar Pradesh in India. Here we offer an extension of ELECTRE III method as two-phase Pythagorean neutrosophic elimination and choice translating reality (PN-ELECTRE-III) method to adapt with fuzzy, ambiguous, unsure, and indeterminate criteria. The Pythagorean neutrosophicnumbers [PNNs] used by the group decision support system of PN-ELECTRE III to measure performance of the alternatives. The options are entirely outclassed in the subsequent stage in view of the past stage's evaluations of them. By defining PNN we describe the technique of indifference threshold, preference threshold and veto threshold functions, which provide a more stable basis to drop outranking relations. By calculating the concordance credibility, discordance credibility and net credibility degrees of each alternative, the ranking module of the PN-ELECTRE III approach is made simpler. In order to confirm the applicability of the strategy suggested in this paper, the location selection problem for solar plants is finally solved.

Keywords: Solar Power Plant, Multi-Criteria Decision-Making, Pythagorean Neutrosophic Sets, ELECTRE-III Method.

1. Introduction

With the expansion in environmental concerns and the exhaustion of non-sustainable power assets, renewable energy sources are well known. Solar energy is one of the most abundant renewable energy sources. However, the location of the solar plant is critical as it affects the efficiency and profitability of the plant. A suitable site for the solar plant should have high solar irradiance, flat terrain, and adequate space. Consequently, choosing the right location for the solar plant is a crucial task. In decision making for selecting the suitable location for the solar plant is a multi-criteria decision-making [MCDM] problem (Akram, Ilyas, and Garg 2020; Akram, Garg, and Zahid 2020). The MCDM problem deals with selecting the best alternatives based on multiple criteria. The ELECTRE-III method is a widely used MCDM method that considers multiple criteria and ranks alternatives based on the criteria(Li and Wang 2007a), although the ELECTRE-III method does not consider uncertainty and vagueness in the decision-making process.

Fuzzy set theory is an extension of the traditional crisp set theory (Zadeh 1965). This makes it a useful tool in MCDM problems, where the criteria can frequently be uncertain or imprecise. By giving the logical framework for fuzzy set [FS], whose distinctive feature is to show cryptic data by the dint of membership function, Zadeh made an extraordinary commitment in this area(Zadeh 1965). In order to rank Sicily's international airports and vendors, respectively, Aleskerov F. and Monjardet B., presented modified versions of the ELECTRE-III process in fuzzy environment (Aleskerov and Monjardet 2002). Gao et, al., analysis of the competitiveness of China's Quanzhou port combined the fuzzy-AHP and ELECTRE-III techniques (Gao et al. 2018). The fuzzy ELECTRE-III method was used by La Fata et. al. (La Fata and other authors 2019), to examine a situation involving Italian public healthcare.

In 1986 (Atanassov 1986), Atanassov developed the basis for a realistic model with a changed structure, namely, intuitionistic fuzzy set [IFS], to explain the ambiguous information using satisfaction and dissatisfaction degrees under the given constraints. With the use of the ELECTRE-III approach for intuitionistic fuzzy models, Wu et al., investigated a case for the selection of the most suitable location for an offshore wind power station(Wu and other authors 2018; Xu, Chen, and Wu 2008). IFS theory is a further extension of the traditional fuzzy set theory. It allows elements to have degrees of membership and non-membership that are not necessarily equal to one another, making it a useful tool in dealing with uncertainty in MCDM problems (Akram, Ilyas, and Al-Kenani 2021). Further Pythagorean fuzzy subsets the extension of IFS, made problems more advanced(Yager and Abbasov 2013; Ren, Xu, and Gou 2016; Umamageswari and Uthra, n.d.; Akram, Dudek, and Ilyas 2019; Akram, Zahid, and Kahraman 2023; Akram, Dudek, and Dar 2019; Zhang and Xu 2014; Akram, Zahid, and Kahraman, n.d.; Akram and Ali 2020; Akram, Ilyas, and Garg 2020; Zhang 2016; Akram, Ilyas, and Al-Kenani 2021).

Neutrosophic set theory [NST]as an extension of the traditional crisp, fuzzy, and intuitionistic fuzzy set theories introduced by Smarandache F., in 1998 (Smarandache 1998). It allows elements to have degrees of membership, degrees of non-membership, and degrees of indeterminacy that are independent of one another, making it a useful tool in dealing with incomplete or inconsistent information in MCDM problems. By introducing a new neutrosophic outranking relation based on the concept of truth-membership, falsity-non-membership, and indeterminacy-membership degrees, the ELECTRE-III method has been further extended to handle neutrosophic sets (Smarandache, Ali, and Khan 2019; Ali and Smarandache 2017; Ye 2018; Abdel-Baset et al., n.d.; Akram, Shumaiza, and Smarandache 2018; Singh, Arora, and Arora 2022; Khatter 2020; Smarandache, n.d.; Rizk-Allah, Hassanien, and Elhoseny 2018; Dat et al. 2019; Kumar et al. 2019).

Recently in 2019 Smarandache and Broumi (Smarandache and Broumi 2019) introduced the Pythagorean neutrosophic set [PNS], which was a further extension of the NST. It allows elements to have three independent values such as truth-membership, and indeterminacy-membership and falsity-membership degrees. PNS are a useful and effective tool to handle incomplete or inconsistent information in MCDM problems. Pythagorean neutrosophic programming [PNP]approach is a generalization of FS theory and NST that can handle uncertain, incomplete, and inconsistent information in the decision-making process(RAJAN and KRISHNASWAMY, n. d.; Jansi, Mohana, and Smarandache 2019b)In the present research problem, we are utilizing PNP approach with the ELECTRE-III technique, which can improve the decision-making process.

In this paper, we propose a two-phase decision-aiding system for the solar plant location problem using the ELECTRE-III method in the PNP approach. The first phase of the proposed system uses the PNP approach to handle uncertain and incomplete information in the decision-making process. In the second phase, the ELECTRE-III method is used to rank the alternatives based on the criteria (Akram, Ilyas, and Al-Kenani 2021). The proposed system can provide decision-makers with a set of feasible alternatives and their ranking based on the criteria.

A case study on green energy in Bundelkhand region of India is conducted to demonstrate the effectiveness of the proposed system. The study considers seven potential sites for the solar plant, and the decision criteria are as *solar abundant, solar radiation*, *flat & open land,high land and construction costs,demand for electricity*, *extreme weather conditions*, *higher elevation from sea level*, *proximity to transmission lines* and *average dust density to the substation.*The results show that the proposed system can provide decision-makers with a set of feasible alternatives and their ranking based on the criteria, which can help decision-makers in selecting the most suitable site for the solar plant.

1.1 Motivation Behind the Current Study

The increasing demand for clean and sustainable energy has led to a surge in the installation of solar power plants (Tahri, Hakdaoui, and Maanan 2015; Uyan 2013). However, identifying the optimal location for a solar plant is a complex problem due to numerous factors such as weather conditions, land availability, infrastructure, and environmental impact. In this context, decision-aiding systems can assist decision-makers in identifying the best location for solar plant installation. This study aims to develop a two-phase decision-aiding system(Akram, Ilyas, and Al-Kenani 2021) using the ELECTRE-III method in the PNPapproach for the solar plant location problem(Abdel-Baset et al., n.d.; Khatter 2020; Kaur and Yadav 2022; Ye 2018; RAJAN and KRISHNASWAMY, n.d.; Smarandache and Broumi 2019; Jansi, Mohana, and Smarandache 2019b; Palanikumar, Arulmozhi, and Jana 2022). The proposed method considers the imprecise and uncertain nature of the decision-making process in the solar plant location problem. A contextual analysis on green energy in Bundelkhand region of India is conducted to demonstrate the applicability and effectiveness of the proposed method.

The consequences of this study can help policymakers and partners in pursuing informed choices in regards to the optimal location for solar plant establishment. This research also contributes to the literature on decision-making under uncertainty using PN-ELECTRE-III method.

1.2 Objectives of Current Investigation

The objective of this investigation is to propose a two-phase decision-aiding system for selecting suitable locations for solar plants in Bundelkhand region of India, using the PN-ELECTRE III method. The proposed system aims to consider various factors such as economic, social, environmental, and technical aspects to select the optimal location for solar plants in Bundelkhand. The first phase of the proposed system involves the development of a PN-ELECTRE III method to evaluate the suitability of potential locations for solar plants. The second phase involves the development of a decision-aiding system to prioritize the locations based on the evaluation results of the first phase. The proposed system will take into account the uncertainties and imprecision in decision-making using PNP.The study will contribute to the field of decision-making in renewable energy by developing a comprehensive decision-aiding system that considers multiple criteria and uncertain information[9, 41, 42]. The proposed system will also provide valuable insights into the selection of optimal locations for solar plants in seven districts as Banda, Chitrakoot, Hamirpur, Jalaun, Jhansi, Lalitpur and Mahoba of Bundelkhand region and help policymakers and investors to make informed decisions.

1.3 Related Research Work

The proposed approach builds on the existing literature on decision-making methods and multi-criteria decision-making in particular. The ELECTRE III method has been widely used in previous research for decision-making in different contexts, such as supply chain management, transportation, and environmental management. For instance, Guitouni and Martel (Guitouni and Martel 1998) applied the ELECTRE III method to select the best location for a landfill site in Quebec, Canada. Similarly, Kaya and Kahraman (Kaya and Kahraman 2010) utilized the ELECTRE-III method to evaluate and rank different wastewater treatment technologies. Moreover, the Pythagorean Neutrosophic programming approach has been used in previous research to address decision-making problems under uncertainty. Wang et al. (Wang et al. 2021) applied the Pythagorean Neutrosophic programming approach to rank different photovoltaic power plant locations in China. Additionally, Abbas et al. (Abbas et al. 2020) used the Pythagorean Neutrosophic programming approach to evaluate and select the best supplier for a manufacturing company.

2. Preliminaries

In this segment, some fundamentals preliminary concept of Neutrosophic sets [NS] (Smarandache 1998), single valued Neutrosophic set [SVNS] (Ye 2014), PNS (Smarandache and Broumi 2019) and PNN are briefly presented which will enable the conversation in the following sections.

Definition 2.1. [50, 51]**:** Let U be a non-empty set. A NS P on U, containing $\phi_P(u)$ as degree of membership, $\varphi_P(u)$ as degree of indeterminacy and $\gamma_P(u)$ as degree of non-membership, defined as

$$P=\{\langle u,\phi_P(u),\varphi_P(u),\gamma_P(u)\rangle : u\in U\}$$

where $\phi_P(u),\varphi_P(u),\gamma_P(u)\in \left]^{-}0,1^{+}\right[$ such that $^{-}0\le \phi_P(u)+\varphi_P(u)+\gamma_P(u)\le 3^{+}$ for all $u\in U$.

Definition 2.2. [50, 51]**:** A SVNSP on a non-empty universal set U is defined as $P=\{\langle u,\phi_P(u),\varphi_P(u),\gamma_P(u)\rangle : u\in U\}$ where $\phi_P(u),\varphi_P(u),\gamma_P(u)\in[0,1]$ such that $0\le \phi_P(u)+\varphi_P(u)+\gamma_P(u)\le 3$ for all $u\in U$, and $\phi_P(u)$ is membership degree function, $\varphi_P(u)$ is indeterminacy degree function and $\gamma_P(u)$ is non-membership degree function.

Definition 2.3. (RAJAN and KRISHNASWAMY, n.d.; Jansi, Mohana, and Smarandache 2019b) 40]: Let Ube a non-empty universal set of discourse. A PNSP on U is defined as

$$P=\{\langle u,\phi_P(u),\varphi_P(u),\gamma_P(u)\rangle : u\in U\}$$

Where $\phi_P(u),\varphi_P(u),\gamma_P(u)\in[0,1]$ such that $0\le(\phi_P(u))^2+(\varphi_P(u))^2+(\gamma_P(u))^2\le 2$ for all $u\in U$, and $\phi_P(u)$ is membership degree function, $\varphi_P(u)$ is indeterminacy degree function and $\gamma_P(u)$ is non-membership degree function. Here truth $(\phi_P(u))$and falsity $(\gamma_P(u))$are dependent components and indeterminacy $(\varphi_P(u))$is an independent component. The triplet $P=(\phi_P(u),\varphi_P(u),\gamma_P(u))$ is called a PNN.

For convenience, we represent a PNN $P=(\phi_P(u),\varphi_P(u),\gamma_P(u))$ as $P=(\phi_P,\varphi_P,\gamma_P)$, throughout in this article.

Definition 2.4.(Jansi, Mohana, and Smarandache 2019a):[Operation] Let three PNN $P=(\phi_P,\varphi_P,\gamma_P)$, $P_1=(\phi_{P_1},\varphi_{P_1},\gamma_{P_1})$ and $P_2=(\phi_{P_2},\varphi_{P_2},\gamma_{P_2})$ then the elementary mathematical operations over these PNNs are defined as:

(i) Complement: $P^C=(\gamma_P,\varphi_P,\phi_P)$

(ii) Union:

$$P_1\cup P_2=\left(\max\{\phi_{P_1},\phi_{P_2}\},\min\{\varphi_{P_1},\varphi_{P_2}\},\min\{\gamma_{P_1},\gamma_{P_2}\}\right)$$

(iii) Intersection:

$$P_1\cap P_2=\left(\min\{\phi_{P_1},\phi_{P_2}\},\max\{\varphi_{P_1},\varphi_{P_2}\},\max\{\gamma_{P_1},\gamma_{P_2}\}\right)$$

(iv) Addition:

$$P_1\oplus P_2=\left(\sqrt{\phi_{P_1}^2+\phi_{P_2}^2-\phi_{P_1}^2\cdot\phi_{P_2}^2},\varphi_{P_1}\cdot\varphi_{P_2},\gamma_{P_1}\cdot\gamma_{P_2}\right)$$

(v) Multiplication:

$$P_1 \oplus P_2 = \left(\phi_{P_1}\cdot\phi_{P_2}, \sqrt{\varphi_{P_1}^2+\varphi_{P_2}^2-\varphi_{P_1}^2\cdot\varphi_{P_2}^2}, \sqrt{\gamma_{P_1}^2+\gamma_{P_2}^2-\gamma_{P_1}^2\cdot\gamma_{P_2}^2}\right)$$

(vi) Scalar Multiplication:

$$r.P = \left(\sqrt{1-\left(1-\phi_P^2\right)^r}, \left(\varphi_P\right)^r, \left(\gamma_P\right)^r\right):\ r>0.$$

(vii) Exponentiation

$$P^r = \left(\left(\phi_P\right)^r, \sqrt{1-\left(1-\varphi_P^2\right)^r}, \sqrt{1-\left(1-\gamma_P^2\right)^r}\right)\ : r>0.$$

Definition 2.5. (Garg and Nancy 2018), [De-Neutrosophication]

(i). Score Function: $s\left(P\right)=\phi_P^2-\varphi_P^2-\gamma_P^2$

(ii). Accuracy Function: $a\left(P\right)=\phi_P^2+\varphi_P^2+\gamma_P^2$

(iii). Normalized Euclidean Distance:

$$d\left(P_1,P_2\right)=\sqrt{\left({\phi_{P_1}}^2-{\phi_{P_2}}^2\right)^2+\left({\varphi_{P_1}}^2-{\varphi_{P_2}}^2\right)^2+\left({\gamma_{P_1}}^2-{\gamma_{P_2}}^2\right)^2}$$

Definition 2.6. (Akram, Ilyas, and Al-Kenani 2021; Garg and Nancy 2018), [Comparison]

(I) If $s(P_1)>s(P_2)$, then $P_1 \succ P_2$ (P_1 is superior to P_2)

(II) If $s(P_1)=s(P_2)$, then

a. If $a(P_1)>a(P_2)$, then $P_1 \succ P_2$ (P_1 is superior to P_2)

b. If $a(P_1)=a(P_2)$, then $P_1 \square P_2$ (P_1 is superior to P_2)

Definition 2.7.(Palani kumar, Arulmozhi, and Jana 2022), [Aggregation]: Let $P_i=\left(\phi_{P_i},\varphi_{P_i},\gamma_{P_i}\right)$, $w=\left(w_1,w_2,w_3,...,w_n\right)$ and $\sum_{i=1}^n w_i=1$

(1) PNWA Operator

$$\begin{aligned} &PNWA_w\left(P_1,P_2,P_3,...,P_n\right) \\ &= w_1P_1\oplus w_2P_2\oplus w_3P_3\oplus...\oplus w_nP_n \\ &= \left(\sqrt{1-\prod_{i=1}^n\left(1-\phi_{P_i}^2\right)^{w_i}}, \prod_{i=1}^n\left(\varphi_{P_i}\right)^{w_i}, \prod_{i=1}^n\left(\gamma_{P_i}\right)^{w_i}\right) \end{aligned} \quad (1)$$

(2) PNWG Operator

$$\begin{aligned} &PNWG_w\left(P_1,P_2,P_3,...,P_n\right) \\ &= w_1P_1\otimes w_2P_2\otimes w_3P_3\otimes...\otimes w_nP_n \\ &= \left(\prod_{i=1}^n\left(\phi_{P_i}\right)^{w_i}, \sqrt{1-\prod_{i=1}^n\left(1-\varphi_{P_i}^2\right)^{w_i}}, \sqrt{1-\prod_{i=1}^n\left(1-\gamma_{P_i}^2\right)^{w_i}}\right) \end{aligned} \quad (2)$$

3. ELECTRE III Method

Let $\Lambda=\left\{\lambda_1,\lambda_2,\lambda_3,...,\lambda_a,...,\lambda_f\right\}$ be a set of available f alternatives and $\mathrm{X}=\left\{\chi_1,\chi_2,\chi_3,...,\chi_b,...,\chi_g\right\}$ be a set of g criteria corresponding to each alternative for a MCGDM problem. A group $\mathrm{E}=\left\{\varepsilon_1,\varepsilon_2,\varepsilon_3,...\varepsilon_t,...\varepsilon_h\right\}$ of h expert or Decision-Maker [DM]allocates the feasibility or performance or the evaluation information of alternative $\lambda_a\in\Lambda$ with respect to criterion $\chi_b\in\mathrm{X}$ as; $\chi_b(\lambda_a)$. The more the alternative satisfy the criterion, the lower or higher the value of $\chi_b(\lambda_a)$, which be subject to upon whether the objective is to minimize or to maximize for the criterion χ_b. Subsequently, the performance/ feasibility information of an alternative λ_a on the basis of multiple criteria will be represented by the vector $\chi\left(\lambda_a\right)=\left\{\chi_1\left(\lambda_a\right),\ \chi_2\left(\lambda_a\right),\ ...,\ \chi_g\left(\lambda_a\right)\right\}$ as all the criteria can have their own importance considering objective of the MCGDM problem thus criteria weight vector will be denoted by $w=\left\{w_1,w_2,w_3,...,w_b,...,w_g\right\}$ such that $\sum_{b=1}^g w_b=1$. Similarly, the importance expert weight vector will be $\ell=\left\{\ell_1,\ell_2,\ell_3,...,\ell_t,...,\ell_h\right\}$ such that $\sum_{t=1}^h \ell_t=1$.

The ranking process of the ELECTRE-III method consists of two modules(Roy 1978)]. After the performance evaluation of alternatives by evaluators or DM's over multiple criteria, the establishment of preference and indifference threshold functions, the determination of concordance and discordance indices, and ultimately the revelation of credibility index come under first module in the formation of an outranking connection. Using outranking relations to deduce a comprehensive feasibility ranking of alternatives makes up the second module.

3.1 Module I: Developing Outranking Relations

In the MCGDM process, an alternative λ_1 outranks another alternative λ_2, represented by $\lambda_1 S\lambda_2$, if there is sufficient evidence to believe that λ_1 is at least as good as λ_2 and there are no compelling counterarguments. The ELECTRE method's fundamental tenet is to establish a preference relation—often referred to as an outranking relation—among the acts assessed across a number of criteria. The basis for establishing the outranking relation $\lambda_1 S\lambda_2$ is provided by the credibility index, which is the degree of outranking. Concordance index and discordance index, computed throughout each criterion $\chi_b\in\mathrm{X}$, are used to calculate the degree of credibility.

3.1.1 Erection of Threshold Functions

The ELECTRE III model's assessment technique include establishing indifference threshold function, preference threshold function and veto threshold function for disclosing concordance and discordance indices, determining the degree of credibility, and ranking the alternatives. Let $q(\chi_b)$ be the indifference threshold function and $p(\chi_b)$ be the preference thresholds function for corresponding criteria χ_b.

Let if for any two given alternatives $\lambda_1, \lambda_2 \in \Lambda$, $\chi(\lambda_1) \geq \chi(\lambda_2)$, then,

$$\chi(\lambda_1) \succ \chi(\lambda_2) + p(\chi(\lambda_2)) \Leftrightarrow \lambda_1 P \lambda_2 \quad (3)$$

$$\chi(\lambda_2) + q(\chi(\lambda_2)) \prec \chi(\lambda_1) \prec \chi(\lambda_2) + p(\chi(\lambda_2)) \Leftrightarrow \lambda_1 Q \lambda_2 \quad (4)$$

$$\chi(\lambda_2) \prec \chi(\lambda_1) \prec \chi(\lambda_2) + q(\chi(\lambda_2)) \Leftrightarrow \lambda_1 I \lambda_2 \quad (5)$$

where $\chi(\lambda)$ is the criterion score value of the alternative λ, , and P signifies strong preference, Q weak preference, and I indifference.

3.1.2 Calculating the Concordance Index of the Assertion $\lambda_1 S \lambda_2$

For each pair of alternatives, the comprehensive concordance index is

$$\Delta(\lambda_1, \lambda_2) = \sum_{b=1}^{g} w_b \Delta_b(\lambda_1, \lambda_2) \quad (6)$$

where w_b represent the weight of b^{th} criteria and $\Delta_b(\lambda_1, \lambda_2)$ represent the partial concordance indices over the criteria χ_b is calculated as

$$\Delta_b(\lambda_1, \lambda_2) = \begin{cases} 0, & \text{if } \chi_b(\lambda_2) - \chi_b(\lambda_1) \succ p(\chi_b) \\ 1, & \text{if } \chi_b(\lambda_2) - \chi_b(\lambda_1) \leq q(\chi_b) \\ \dfrac{p(\chi_b) - (\chi_b(\lambda_2) - \chi_b(\lambda_1))}{p(\chi_b) - q(\chi_b)}, & \text{otherwise} \end{cases} \quad (7)$$

Thus $0 \leq \Delta_b(\lambda_1, \lambda_2) \leq 1$.

3.1.3 Calculating the Discordance Index of the Assertion $\lambda_1 S \lambda_2$

For each criterion, the discordance index $\nabla_b(\lambda_1, \lambda_2)$ is calculated

$$\nabla_b(\lambda_1, \lambda_2) = \begin{cases} 0, & \text{if } \chi_b(\lambda_2) - \chi_b(\lambda_1) \leq p(\chi_b) \\ 1, & \text{if } \chi_b(\lambda_2) - \chi_b(\lambda_1) \succ v(\chi_b) \\ \dfrac{(\chi_b(\lambda_2) - \chi_b(\lambda_1)) - p(\chi_b)}{v(\chi_b) - p(\chi_b)}, & \text{otherwise} \end{cases} \quad \textbf{(8)}$$

Thus $0 \leq \nabla_b(\lambda_1, \lambda_2) \leq 1$.

3.1.4Disclosure of Credibility Index

The credibility index, denoted by the notation $\pi(\lambda_1, \lambda_2)$, is used to determine the degree of outranking relation $\lambda_1 S \lambda_2$ is defined as

$$\pi(\lambda_1, \lambda_2) = \begin{cases} \Delta(\lambda_1, \lambda_2), & \text{if } \nabla_b(\lambda_1, \lambda_2) \leq \Delta(\lambda_1, \lambda_2), \forall\, b \in \tau \\ \Delta(\lambda_1, \lambda_2) \times \prod_{b \in \tau'} \dfrac{(1 - \nabla_b(\lambda_1, \lambda_2))}{(1 - \Delta(\lambda_1, \lambda_2))}, & \text{otherwise} \end{cases} \quad (9)$$

where $\tau' = \{b \in \tau : \nabla_b(\lambda_1, \lambda_2) > \Delta(\lambda_1, \lambda_2)\}$.

3.2 Module II: The Exploitation of Outranking Relations

The standard ranking approach of ELECTRE III employs a structured algorithm via two intermediate ranking procedures, one of which is descending distillation, where the alternatives are ranked from best to worst, and the other of which is based on ascending order from worst to best alternative (ascending distillation). In contrast, a new ranking approach based on the introduction of three concepts such as *the concordance credibilitydegree, the discordance credibility degree, and the net credibility degree*is used, According to Li and Wang (Li and Wang 2007b)

1. For each alternative, the concordance credibility degree defined as:

$$\eta^+(\lambda_a) = \sum_{\lambda_b \in \Lambda} \pi(\lambda_a, \lambda_b), \ \forall\ \lambda_a \in \Lambda. \quad (10)$$

The concordance credibility degree represents outranked λ_a (demonstrating how λ_a outperforms over all of its alternatives in Λ).

2. For each alternative, the discordance credibility degree defined as:

$$\eta^-(\lambda_a) = \sum_{\lambda_b \in \Lambda} \pi(\lambda_b, \lambda_a), \ \forall\ \lambda_a \in \Lambda. \quad (11)$$

The discordance credibility degree represents outranked λ_b (demonstrating how λ_b outperforms over all of its alternatives in Λ).

3. For each alternative, the net credibility degree defined as:

$$\eta(\lambda_a) = \eta^+(\lambda_a) - \eta^-(\lambda_a), \ \forall\ \lambda_a \in \Lambda. \quad (12)$$

The attractiveness of alternative λ_a increases with the value of net credibility degree $\eta(\lambda_a)$. Consequently, based on the level of net credibility, the possible alternatives can be ranked in decreasing order.

4. Two-Phase Pythagorean Neutrosophic ELECTRE III Method (Algorithm)

In this part, the two-phase PN-ELECTRE IIIgroup decision support system is created by combining the PNSs and traditional ELECTRE-III approach.

InPythagorean Neutrosophicenvironment, let for a multi-criteria group decision making [MCGDM] problem, $\Lambda=\{\lambda_1,\lambda_2,\lambda_3,...,\lambda_a,...,\lambda_f\}$ be a set of available f alternatives and $X=\{\chi_1,\chi_2,\chi_3,...,\chi_b,...,\chi_g\}$ be a set of g criteria assigning to each alternative. A group $E=\{\varepsilon_1,\varepsilon_2,\varepsilon_3,...\varepsilon_t,...\varepsilon_h\}$ of h expert or DM assigns the feasibility information of alternative $\lambda_a\in\Lambda$ with respect to criterion $\chi_b\in X$ as; $\chi_b(\lambda_a)$. All the criteria can have their own and unequal importance considering objective of the MCGDM problem thus criteria weight vector will be denoted by $w=\{w_1,w_2,w_3,...,w_b,...,w_g\}$ such that $\sum_{b=1}^{g} w_b=1$. Similarly, the importance expert weight vector will be $\ell=\{\ell_1,\ell_2,\ell_3,...,\ell_t,...,\ell_h\}$ such that $\sum_{t=1}^{h}\ell_t=1$. Let the subscript set of criterions i.e. $\tau=\{1,2,3,...,g\}$.

4.1 Phase I: Pythagorean Neutrosophic Evaluation Phase

Step-1.
First, we establish some linguistic variables/terms in the form of PNN for the evaluation of, feasibility ratings of alternatives, importance weights of criterion, importance weights of experts and establishment of threshold functions.

Step-2.
Systematically assessing each alternative $\lambda_a\,(a=1,2,3,...,f)$ with respect to each criterion $\chi_b\,(b=1,2,3,...,g)$. Expert $\varepsilon_t\,(t=1,2,3,...,h)$ provides his/her evaluation information in the form of Pythagorean Neutrosophicdecision matrix

[PNDM] $M^{(t)}=[M_{ab}^{(t)}]_{f\times g}$, as in table 1.where $M_{ab}^{(t)}=\left(\phi_{M_a}^{(t)}(\chi_b),\varphi_{M_a}^{(t)}(\chi_b),\gamma_{M_a}^{(t)}(\chi_b)\right)$ is the PNN allocated by the DM ε_t, with $\phi_{M_a}^{(t)}(\chi_b)$ is membership degree function, $\varphi_{M_a}^{(t)}(\chi_b)$ is indeterminacy degree function and $\gamma_{M_a}^{(t)}(\chi_b)$ is non-membership degree function. Here truth $\left(\phi_{M_a}^{(t)}(\chi_b)\right)$ and falsity $\left(\gamma_{M_a}^{(t)}(\chi_b)\right)$ are dependent components and indeterminacy $\left(\varphi_{M_a}^{(t)}(\chi_b)\right)$ is an independent component.

Table 1: PNDM by DM

$M^{(t)}$	χ_1	χ_2	$\cdots$	χ_g
λ_1	$\left(\phi_{M_1}^{(t)}(\chi_1),\varphi_{M_1}^{(t)}(\chi_1),\gamma_{M_1}^{(t)}(\chi_1)\right)$	$\left(\phi_{M_1}^{(t)}(\chi_2),\varphi_{M_1}^{(t)}(\chi_2),\gamma_{M_1}^{(t)}(\chi_2)\right)$	$\cdots$	$\left(\phi_{M_1}^{(t)}(\chi_g),\varphi_{M_1}^{(t)}(\chi_g),\gamma_{M_1}^{(t)}(\chi_g)\right)$
λ_2	$\left(\phi_{M_2}^{(t)}(\chi_1),\varphi_{M_2}^{(t)}(\chi_1),\gamma_{M_2}^{(t)}(\chi_1)\right)$	$\left(\phi_{M_2}^{(t)}(\chi_2),\varphi_{M_2}^{(t)}(\chi_2),\gamma_{M_2}^{(t)}(\chi_2)\right)$	$\cdots$	$\left(\phi_{M_2}^{(t)}(\chi_g),\varphi_{M_2}^{(t)}(\chi_g),\gamma_{M_2}^{(t)}(\chi_g)\right)$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
λ_f	$\left(\phi_{M_f}^{(t)}(\chi_1),\varphi_{M_f}^{(t)}(\chi_1),\gamma_{M_f}^{(t)}(\chi_1)\right)$	$\left(\phi_{M_f}^{(t)}(\chi_2),\varphi_{M_f}^{(t)}(\chi_2),\gamma_{M_f}^{(t)}(\chi_2)\right)$	$\cdots$	$\left(\phi_{M_f}^{(t)}(\chi_g),\varphi_{M_f}^{(t)}(\chi_g),\gamma_{M_f}^{(t)}(\chi_g)\right)$

Step-3. Weight of t^{th} expert can be determined by the following Eq.

$$\ell_t=\frac{\phi_t+\gamma_t\left(\dfrac{\phi_t}{\phi_t+\varphi_t}\right)}{\sum_{t=1}^{h}\left(\phi_t+\gamma_t\left(\dfrac{\phi_t}{\phi_t+\varphi_t}\right)\right)},\tag{13}$$

Where the ℓ_t satisfy the normalized condition $\sum_{t=1}^{h}\ell_t=1$.

Step-4. The distinct opinions of DM or experts required to be combined into a collective opinion to construct aggregated PNDM $\ddot{M}=\left(\ddot{M}_{ab}\right)_{f\times g}$ by using Pythagorean Neutrosophic weighted averaging [PNWA] operator (Palanikumar, Arulmozhi, and Jana 2022; Garg and Nancy 2018). Where $M^{(t)}=\left(M_{ab}^{(t)}\right)_{f\times g}$ is the PNDMof the expert ε_t.

$$\begin{aligned}\ddot{M}_{ab}&=PNWA_\ell\left(M_{ab}^{(1)},M_{ab}^{(2)},M_{ab}^{(3)},...,M_{ab}^{(h)}\right)\\&=\ell_1M_{ab}^{(1)}\oplus\ell_2M_{ab}^{(2)}\oplus\ell_3M_{ab}^{(3)}\oplus...\oplus\ell_hM_{ab}^{(h)}\\&=\left(\sqrt{1-\prod_{t=1}^{h}\left(1-\left(\phi_{ab}^{(t)}\right)^2\right)^{\ell_t}},\prod_{t=1}^{h}\left(\varphi_{ab}^{(t)}\right)^{\ell_t},\prod_{t=1}^{h}\left(\gamma_{ab}^{(t)}\right)^{\ell_t}\right)\end{aligned}\tag{14}$$

where $\ddot{M}_{ab}=\left(\phi_{\ddot{M}_a}(\chi_b),\varphi_{\ddot{M}_a}(\chi_b),\gamma_{\ddot{M}_a}(\chi_b)\right)$, $a=1,2,3,...,f$ and $b=1,2,3,...,g$ consequently, the matrix $\ddot{M}$ can be ready as in table 2.

Table 2: Aggregated PNDM

$\ddot{M}$	χ_1	χ_2	$\cdots$	χ_g
λ_1	$\left(\phi_{\ddot{M}_1}(\chi_1),\varphi_{\ddot{M}_1}(\chi_1),\gamma_{\ddot{M}_1}(\chi_1)\right)$	$\left(\phi_{\ddot{M}_1}(\chi_2),\varphi_{\ddot{M}_1}(\chi_2),\gamma_{\ddot{M}_1}(\chi_2)\right)$	$\cdots$	$\left(\phi_{\ddot{M}_1}(\chi_g),\varphi_{\ddot{M}_1}(\chi_g),\gamma_{\ddot{M}_1}(\chi_g)\right)$
λ_2	$\left(\phi_{\ddot{M}_2}(\chi_1),\varphi_{\ddot{M}_2}(\chi_1),\gamma_{\ddot{M}_2}(\chi_1)\right)$	$\left(\phi_{\ddot{M}_2}(\chi_2),\varphi_{\ddot{M}_2}(\chi_2),\gamma_{\ddot{M}_2}(\chi_2)\right)$	$\cdots$	$\left(\phi_{\ddot{M}_2}(\chi_g),\varphi_{\ddot{M}_2}(\chi_g),\gamma_{\ddot{M}_2}(\chi_g)\right)$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
λ_f	$\left(\phi_{\ddot{M}_f}(\chi_1),\varphi_{\ddot{M}_f}(\chi_1),\gamma_{\ddot{M}_f}(\chi_1)\right)$	$\left(\phi_{\ddot{M}_f}(\chi_2),\varphi_{\ddot{M}_f}(\chi_2),\gamma_{\ddot{M}_f}(\chi_2)\right)$	$\cdots$	$\left(\phi_{\ddot{M}_f}(\chi_g),\varphi_{\ddot{M}_f}(\chi_g),\gamma_{\ddot{M}_f}(\chi_g)\right)$

Step-5. Let X_B and X_C represent the corresponding collections of criteria that are of the benefit-type and cost-types. The aggregated PNDM, $\ddot{M}=\left(\ddot{M}_{ab}\right)_{f\times g}$, can be converted into the normalized aggregated PNDM, $M=\left(M_{ab}\right)_{f\times g}$ which displays the evaluation information of each alternative with respect to each benefit or cost criterion, in standard form, for additional calculations. PNN for M_{ab} can describe as follows:

$$M_{ab}=\left(\phi_{M_a}(\chi_b),\varphi_{M_a}(\chi_b),\gamma_{M_a}(\chi_b)\right)$$
$$=\begin{cases}\ddot{M}_{ab}=\left(\phi_{\ddot{M}_a}(\chi_b),\varphi_{\ddot{M}_a}(\chi_b),\gamma_{\ddot{M}_a}(\chi_b)\right), & \text{if } \chi_b\in X_B\\ \left(\ddot{M}_{ab}\right)^C=\left(\gamma_{\ddot{M}_a}(\chi_b),\varphi_{\ddot{M}_a}(\chi_b),\phi_{\ddot{M}_a}(\chi_b)\right), & \text{if } \chi_b\in X_C\end{cases} \tag{15}$$

Table 3 demonstrates how the matrix M is built.

Table 3: Normalized Aggregated PNDM

M	χ_1	χ_2	$\cdots$	χ_g
λ_1	$\left(\phi_{M_1}(\chi_1),\varphi_{M_1}(\chi_1),\gamma_{M_1}(\chi_1)\right)$	$\left(\phi_{M_1}(\chi_2),\varphi_{M_1}(\chi_2),\gamma_{M_1}(\chi_2)\right)$	$\cdots$	$\left(\phi_{M_1}(\chi_g),\varphi_{M_1}(\chi_g),\gamma_{M_1}(\chi_g)\right)$
λ_2	$\left(\phi_{M_2}(\chi_1),\varphi_{M_2}(\chi_1),\gamma_{M_2}(\chi_1)\right)$	$\left(\phi_{M_2}(\chi_2),\varphi_{M_2}(\chi_2),\gamma_{M_2}(\chi_2)\right)$	$\cdots$	$\left(\phi_{M_2}(\chi_g),\varphi_{M_2}(\chi_g),\gamma_{M_2}(\chi_g)\right)$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
λ_f	$\left(\phi_{M_f}(\chi_1),\varphi_{M_f}(\chi_1),\gamma_{M_f}(\chi_1)\right)$	$\left(\phi_{M_f}(\chi_2),\varphi_{M_f}(\chi_2),\gamma_{M_f}(\chi_2)\right)$	$\cdots$	$\left(\phi_{M_f}(\chi_g),\varphi_{M_f}(\chi_g),\gamma_{M_f}(\chi_g)\right)$

Step-6. Not all criteria might have equally significant. Let $w_b^{(t)}=\left(\phi_w^{(t)}(\chi_b),\varphi_w^{(t)}(\chi_b),\gamma_w^{(t)}(\chi_b)\right)$ represent the PNN that the expert ε_t assigned for the relative weight of criterion χ_b. By aggregating the opinions of experts on χ_b, determine the PN weight $w_b=\left(\phi_w(\chi_b),\varphi_w(\chi_b),\gamma_w(\chi_b)\right)$ as follows:

$$w_b=PNWA_\ell\left(w_b^{(1)},w_b^{(2)},w_b^{(3)},...,w_b^{(h)}\right)$$
$$=\ell_1 w_b^{(1)}\oplus\ell_2 w_b^{(2)}\oplus\ell_3 w_b^{(3)}\oplus...\oplus\ell_h w_b^{(h)}$$
$$=\left(\sqrt{1-\prod_{t=1}^{h}\left(1-\left(\phi_b^{(t)}\right)^2\right)^{\ell_t}},\prod_{t=1}^{h}\left(\varphi_b^{(t)}\right)^{\ell_t},\prod_{t=1}^{h}\left(\gamma_b^{(t)}\right)^{\ell_t}\right) \tag{16}$$

Thus, the following criteria weight row matrix can be obtained.

$$w_b=\begin{pmatrix}\left(\phi_w(\chi_1),\varphi_w(\chi_1),\gamma_w(\chi_1)\right)\\ \left(\phi_w(\chi_2),\varphi_w(\chi_2),\gamma_w(\chi_2)\right)\\ \cdots\\ \cdots\\ \left(\phi_w(\chi_g),\varphi_w(\chi_g),\gamma_w(\chi_g)\right)\end{pmatrix}^T \tag{17}$$

It is established the weight matrix $w=\left\{w_1,w_2,w_3,...,w_b,...,w_g\right\}$ for the criteria. The following equation is used to determine the normalized weights of each criterion based on the total weights of the criteria w_b, which adhere to the condition $\sum_{b=1}^{g}w'_b=1$.

$$w'_b=\frac{\phi_w(\chi_b)+\gamma_w(\chi_b)\left(\dfrac{\phi_w(\chi_b)}{\phi_w(\chi_b)+\varphi_w(\chi_b)}\right)}{\sum_{b=1}^{g}\left(\phi_w(\chi_b)+\gamma_w(\chi_b)\left(\dfrac{\phi_w(\chi_b)}{\phi_w(\chi_b)+\varphi_w(\chi_b)}\right)\right)} \tag{18}$$

Step-7. The weighted normalized aggregated PNDM, $\hat{M}=\left(\hat{M}_{ab}\right)_{f\times g}$ is created as shown in table 4 in the order of integrating the data from the normalized aggregated PNDM and the criteria weight matrix $\hat{M}_{ab}=\left(\phi_{\hat{M}_a}(\chi_b),\varphi_{\hat{M}_a}(\chi_b),\gamma_{\hat{M}_a}(\chi_b)\right)$ may be generated by using the specified multiplication operator (Zhang and Xu 2014),

$$\hat{M}_{ab}=\left(\phi_{M_a}(\chi_b),\varphi_{M_a}(\chi_b),\gamma_{M_a}(\chi_b)\right)\otimes\left(\phi_w(\chi_b),\varphi_w(\chi_b),\gamma_w(\chi_b)\right)$$
$$=\Big(\phi_{M_a}(\chi_b)\cdot\phi_w(\chi_b),\sqrt{\varphi_{M_a}^2(\chi_b)+\varphi_w^2(\chi_b)-\varphi_{M_a}^2(\chi_b)\cdot\varphi_w^2(\chi_b)},$$
$$\sqrt{\gamma_{M_a}^2(\chi_b)+\gamma_w^2(\chi_b)-\gamma_{M_a}^2(\chi_b)\cdot\gamma_w^2(\chi_b)}\Big) \tag{19}$$

Table 4: Weighted Normalized Aggregated PNDM

$\hat{M}$	χ_1	χ_2	$\cdots$	χ_g
λ_1	$\left(\phi_{\hat{M}_1}(\chi_1),\varphi_{\hat{M}_1}(\chi_1),\gamma_{\hat{M}_1}(\chi_1)\right)$	$\left(\phi_{\hat{M}_1}(\chi_2),\varphi_{\hat{M}_1}(\chi_2),\gamma_{\hat{M}_1}(\chi_2)\right)$	$\cdots$	$\left(\phi_{\hat{M}_1}(\chi_g),\varphi_{\hat{M}_1}(\chi_g),\gamma_{\hat{M}_1}(\chi_g)\right)$
λ_2	$\left(\phi_{\hat{M}_2}(\chi_1),\varphi_{\hat{M}_2}(\chi_1),\gamma_{\hat{M}_2}(\chi_1)\right)$	$\left(\phi_{\hat{M}_2}(\chi_2),\varphi_{\hat{M}_2}(\chi_2),\gamma_{\hat{M}_2}(\chi_2)\right)$	$\cdots$	$\left(\phi_{\hat{M}_2}(\chi_g),\varphi_{\hat{M}_2}(\chi_g),\gamma_{\hat{M}_2}(\chi_g)\right)$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
λ_f	$\left(\phi_{\hat{M}_f}(\chi_1),\varphi_{\hat{M}_f}(\chi_1),\gamma_{\hat{M}_f}(\chi_1)\right)$	$\left(\phi_{\hat{M}_f}(\chi_2),\varphi_{\hat{M}_f}(\chi_2),\gamma_{\hat{M}_f}(\chi_2)\right)$	$\cdots$	$\left(\phi_{\hat{M}_f}(\chi_g),\varphi_{\hat{M}_f}(\chi_g),\gamma_{\hat{M}_f}(\chi_g)\right)$

4.2 Phase II: Pythagorean Neutrosophic Ranking Phase (PN-ELECTRE-III)

The first phase of the Pythagorean decision support system collects the PN assessment data for each alternative, and the second step uses the PN-ELECTRE-III approach, which uses the aggregated evaluations to produce the whole ranking of alternatives.

4.2.1 Module I: Developing Outranking Relations

Step-8. For each criterion χ_b, determine the preference threshold values $p(\chi_b)$ and indifference threshold values $q(\chi_b)$, as shown in section 3.1.1.

Step-9. The partial concordance indices (X. Peng and Yang 2015), $\Delta_b=\left[\Delta_b(\lambda_i,\lambda_j)\right]_{f\times f},\left(i,j=1,2,3,...,f,i\neq j\right)$, $\left(b=1,2,3,...,g\right)$ and over each criterion $\chi_b\in$ X can be obtained using Eq. (7), in table 5 as follows:

Table 5: Partial concordance indices over each criterion

Δ_b	λ_1	λ_2	$\cdots$	λ_{f-1}	λ_f
λ_1	$-$	$\Delta_b(\lambda_1,\lambda_2)$	$\cdots$	$\Delta_b(\lambda_1,\lambda_{f-1})$	$\Delta_b(\lambda_1,\lambda_f)$
λ_2	$\Delta_b(\lambda_2,\lambda_1)$	$-$	$\cdots$	$\Delta_b(\lambda_2,\lambda_{f-1})$	$\Delta_b(\lambda_2,\lambda_f)$
$\vdots$	$\vdots$	$\vdots$	$-$	$\vdots$	$\vdots$
λ_{f-1}	$\Delta_b(\lambda_{f-1},\lambda_1)$	$\Delta_b(\lambda_{f-1},\lambda_2)$	$\cdots$	$-$	$\Delta_b(\lambda_{f-1},\lambda_f)$
λ_f	$\Delta_b(\lambda_f,\lambda_1)$	$\Delta_b(\lambda_f,\lambda_2)$	$\cdots$	$\Delta_b(\lambda_f,\lambda_{f-1})$	$-$

and after that for each pair of alternatives, the comprehensive concordance index $\Delta=\left[\Delta_{ij}\right]_{f\times f},\left(i,j=1,2,3,...,f,i\neq j\right)$ is calculated using Eq. (6), in table 6 as follows:

Table 6: Comparative concordance index

Δ	λ_1	λ_2	$\cdots$	λ_{f-1}	λ_f
λ_1	$-$	Δ_{12}	$\cdots$	$\Delta_{1(f-1)}$	Δ_{1f}
λ_2	Δ_{21}	$-$	$\cdots$	$\Delta_{2(f-1)}$	Δ_{2f}
$\vdots$	$\vdots$	$\vdots$	$-$	$\vdots$	$\vdots$
λ_{f-1}	$\Delta_{(f-1)1}$	$\Delta_{(f-1)2}$	$\cdots$	$-$	$\Delta_{(f-1)f}$
λ_f	Δ_{f1}	Δ_{f2}	$\cdots$	$\Delta_{f(f-1)}$	$-$

Step-10. For each criterion, the discordance index $\nabla_b=\left[\nabla_b(\lambda_i,\lambda_j)\right]_{f\times f},\left(i,j=1,2,3,...,f,i\neq j\right)$ and $\left(b=1,2,3,...,g\right)$ is calculated using Eq. (8), in table 7 as follows:

Table 7: Discordance index over each criterion

∇_b	λ_1	λ_2	$\cdots$	λ_{f-1}	λ_f
λ_1	$-$	$\nabla_b(\lambda_1,\lambda_2)$	$\cdots$	$\nabla_b(\lambda_1,\lambda_{f-1})$	$\nabla_b(\lambda_1,\lambda_f)$
λ_2	$\nabla_b(\lambda_2,\lambda_1)$	$-$	$\cdots$	$\nabla_b(\lambda_2,\lambda_{f-1})$	$\nabla_b(\lambda_2,\lambda_f)$
$\vdots$	$\vdots$	$\vdots$	$-$	$\vdots$	$\vdots$
λ_{f-1}	$\nabla_b(\lambda_{f-1},\lambda_1)$	$\nabla_b(\lambda_{f-1},\lambda_2)$	$\cdots$	$-$	$\nabla_b(\lambda_{f-1},\lambda_f)$
λ_f	$\nabla_b(\lambda_f,\lambda_1)$	$\nabla_b(\lambda_f,\lambda_2)$	$\cdots$	$\nabla_b(\lambda_f,\lambda_{f-1})$	$-$

Step-11. The credibility index, denoted by the notation $\pi=\left[\pi_{ij}\right]_{f\times f},\left(i,j=1,2,3,...,f,i\neq j\right)$,is used to determine the degree of outranking relation $\lambda_1 S\lambda_2$ can be determine using Eq. (9).in table 8 as follows:

Table 8: Credibility index

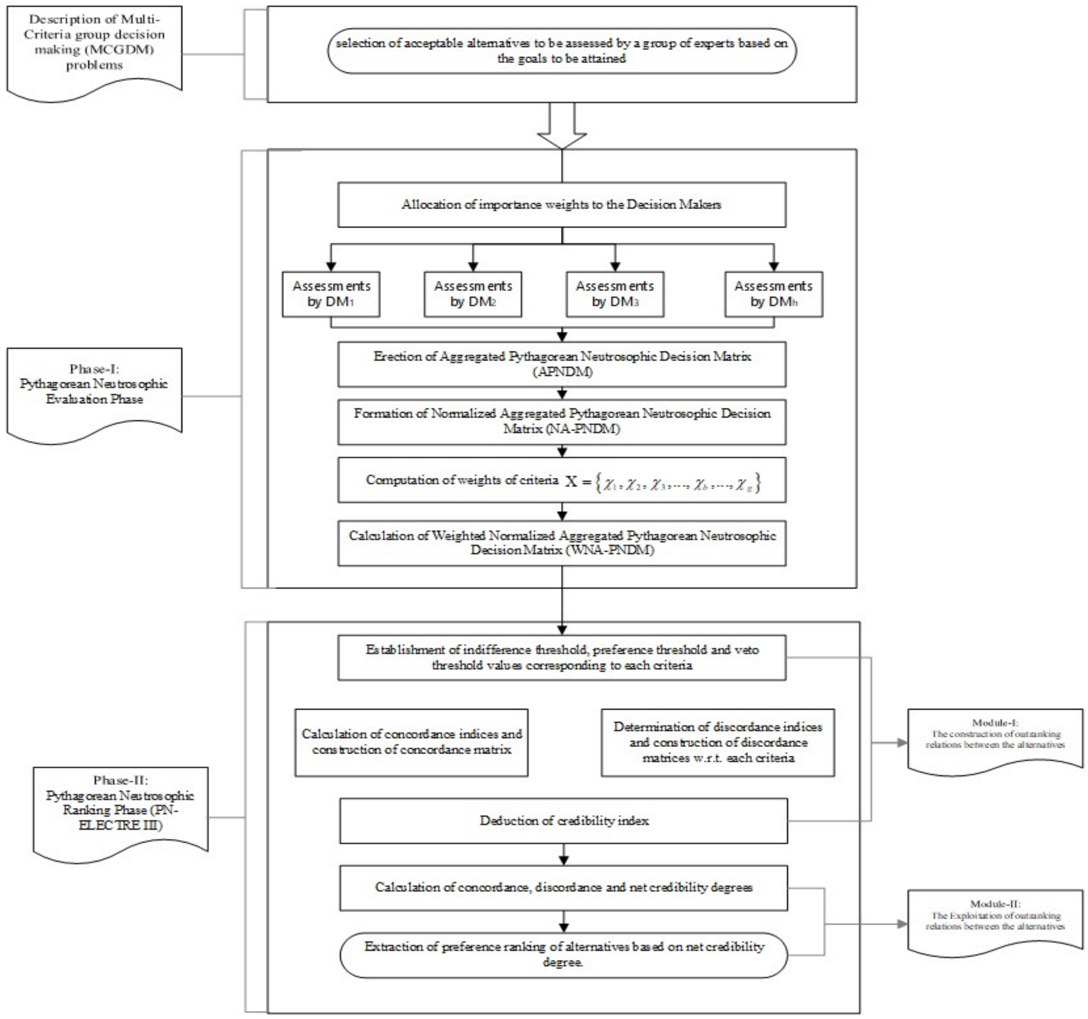
π	λ_1	λ_2	$\cdots$	λ_{f-1}	λ_f
λ_1	$-$	π_{12}	$\cdots$	$\pi_{1(f-1)}$	π_{1f}
λ_2	π_{21}	$-$	$\cdots$	$\pi_{2(f-1)}$	π_{2f}
$\vdots$	$\vdots$	$\vdots$	$-$	$\vdots$	$\vdots$
λ_{f-1}	$\pi_{(f-1)1}$	$\pi_{(f-1)2}$	$\cdots$	$-$	$\pi_{(f-1)f}$
λ_f	π_{f1}	π_{f2}	$\cdots$	$\pi_{f(f-1)}$	$-$

4.2.2 Module II: The Exploitation of Outranking Relations

To get the comprehensive preference ranking of alternatives, compute the concordance credibility degree, discordance credibility degree, and net credibility degree as described in section 3.2.

4.3 Algorithm Diagram:

Figure1: Algorithm diagram of the two-phase group decision-supporting system inorder to provide a step-by-step process for problem-solving.



5. Case Study: Solar Power Plant Location Selection Problem

Bundelkhand is a region in central India, covering parts of Uttar Pradesh and Madhya Pradesh. Bundelkhand region has a high potential for solar power generation due to its abundant sunlight and vast areas of flat land. According to the India meteorological department [IMD], Bundelkhand region falls under the "Hot and Dry" climate zone, which is characterized by high temperatures and low humidity. The region receives an average of 300-325 days of sunshine per year, making it an ideal location for solar power generation.In recent years, the government of India has also taken various initiatives to promote solar power generation in the region. The region has been identified as a potential hotspot for solar power development under the National Solar Mission.

Uttar Pradesh has a total installed solar capacity of around 29.858 GW, of which Bundelkhand region's contribution included. However, it is worth noting that the Uttar Pradesh new and renewable energy development agency [UPNEDA] has been actively promoting solar power projects in the region. In 2018, the UPNEDA invited bids for the development of a 500 MW solar park in Bundelkhand, which would have been one of the largest solar parks in the country. Furthermore, in 2019, the UPNEDA invited bids for the development of 1,000 MW of solar power projects across the state, including in Bundelkhand region.

This section identifies a case study that focuses on solving an MCGDM problem in order to highlight the applicability of the suggested technique in realistic decision-making situations. This study is conducted by one of the Indian NGOs working for solar energy in Bundelkhand region in Uttar Pradesh, INDIA. The organization, which is involved in various activities such as promoting renewable energy policies, conducting research on renewable energy technologies, providing training and awareness programs, implementing renewable energy projects, and development of solar power park/plants projects in seven districts of Bundelkhand region.

5.1 Available Alternatives

In this study, the districts that fall under the Bundelkhand region in Uttar Pradesh are taken as alternatives $\Lambda = \{\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6, \lambda_7\}$

Map 1: Bundelkhand Region of Uttar Pradesh

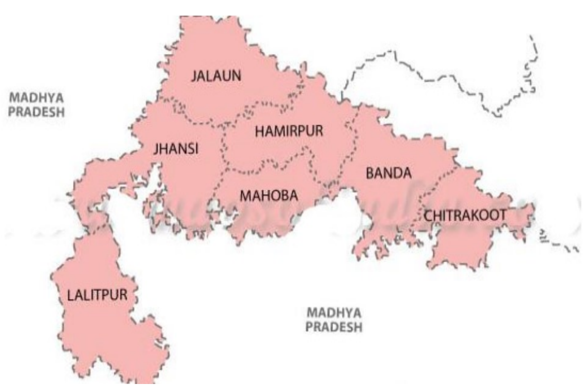


Figure 1: Bundelkhand Region of Uttar Pradesh (Source

Table 9: Available Location(Alternatives) in Seven District of Bundelkhand Region

S.l.	Alternative City Name	Alternative Code
1	Banda	λ_1
2	Chitrakoot	λ_2
3	Hamirpur	λ_3
4	Jalaun	λ_4
5	Jhansi	λ_5
6	Lalitpur	λ_6
7	Mahoba	λ_7

5.2. Selection of Criteria

One of the important issues in MCDM analysis is criteria selection. The main criteria that affect solar power plant location selection are economic, geographic and environmental, technical, and social. Choosing the right criteria is crucial to analyse and get accurate results. There are several favourable/ Benefit-type/ Positive (+) and unfavourable/ Cost-type/ Negative (-) criteria that can make a location suitable/unsuitable for a solar power plant. Here are some of the top criteria $X = \{\chi_1, \chi_2, \chi_3, \chi_4, \chi_5, \chi_6, \chi_7, \chi_8\}$:

1. **Abundant Solar Radiation (+):** The first and foremost factor is the availability of solar radiation. Solar power plants require a significant amount of sunlight to generate electricity. Locations with high levels of annual solar radiation or high numbers of annual sunshine hours are ideal for solar power plants.
2. **Flat& open land (+):** Solar power plants require large, open spaces to accommodate solar panels. Flat land is ideal as it requires less grading and construction work, reducing the cost of building the solar power plant.
3. **High land and construction costs (-):** Solar power plants require large, flat spaces that are expensive to develop. Locations with high land and construction costs may not be financially viable for solar power plants.
4. **Demand for Electricity (+):** The population should have a sufficient demand for electricity to justify the installation of a solar power plant. Areas with low population density or low electricity consumption may not be suitable for large-scale solar power plants.
5. **Extreme weather conditions (-):** Extreme weather conditions such as hurricanes, tornadoes, or heavy snowfall can damage solar panels or disrupt the generation of electricity. Locations with high levels of extreme weather conditions may not be ideal for solar power plants.
6. **Higher elevation from sea level**(+): At higher elevations, the air is thinner, which can lead to lower air density and less atmospheric absorption of solar radiation. This can result in higher solar irradiance values and more direct sunlight reaching the solar panels. Additionally, the temperature at higher elevations can be lower, which can help to reduce the operating temperature of the solar panels and increase their efficiency.
7. **Proximity to transmission lines (+):** Solar power plants generate electricity that needs to be transmitted to the grid. Locations near transmission lines reduce the cost of connecting the solar power plant to the grid.
8. **Average Dust Density (-):**Dust density is a measure of the amount of dust particles in the air, and it can have an impact on solar panel efficiency. The presence of dust particles on the surface of the solar panels can reduce the amount of sunlight that reaches the cells, thereby reducing their efficiency.

Table 10: List of Most Effective Area

S.l.	Criteria Name	Unit	Criteria Code	Type	Source
1	Abundant Solar Radiation	W/m²	χ_1	+ve	https://mausam.imd.gov.in/
2	Flat, Open Land	m²	χ_2	+ve	https://mausam.imd.gov.in/
3	High Land & Construction Cost	Cost/m²	χ_3	-ve	https://ldo.gov.in/Index.aspx
4	Demand for Electricity	kW/Unit	χ_4	+ve	https://www.upenergy.in/
5	Extreme weather conditions	–	χ_5	-ve	https://mausam.imd.gov.in/
6	Higher elevation from sea level	km	χ_6	+ve	https://sealevel.nasa.gov/
7	Proximity to transmission lines	km	χ_7	+ve	https://www.upenergy.in/
8	Average dust density	mg/m³	χ_8	-ve	https://www.mines.gov.in/

5.3. Stepwise Procedure

The whole PN-ELECTRE III process is used in the phases that follow to find the best location for the installation of solar power plant/park unit.

5.3.1Phase I: Pythagorean Neutrosophic Evaluation Phase

Step-1:*Setting-up of Linguistic terms/variables*- By using the decision support system of the suggested technique to solve the aforementioned problem, importance of weight degree to eight criteria and four experts are allocated in the form of linguistic terms/variable that are specified by PNNs as in table 11,

Table 11: Linguistic Terms for Importance Weights Rating of Criteria and Experts

Linguistic terms	Code	PNNs
Very High	VH	(0.92, 0.25, 0.11)
High	H	(0.78, 0.35, 0.24)
Fairly High	FH	(0.64, 0.42, 0.37)
Medium	M	(0.50, 0.55, 0.50)
Fairly Low	FL	(0.36, 0.74, 0.63)
Low	L	(0.22, 0.85, 0.76)
Very Low	VL	(0.08, 0.90, 0.89)

In table 12, specialists independently assess each location's feasibility/performance and threshold functions based on eight criteria, and the performance scores are presented using linguistic terms/variable shown.

Table 12: Linguistic Terms for Feasibility Rating of Alternative and Threshold Functions

Linguistic terms	Code	PNNs
Extremely Feasible	EF	(0.99, 0.05, 0.01)
Very Very Feasible	VVF	(0.95, 0.35, 0.15)
Very Feasible	VF	(0.90, 0.42, 0.25)
Feasible	F	(0.80, 0.55, 0.35)
Medium Feasible	MF	(0.70, 0.74, 0.40)
Medium	M	(0.55, 0.85, 0.45)
Medium Unfeasible	MU	(0.45, 0.90, 0.55)
Unfeasible	U	(0.40, 0.55, 0.70)
Very Unfeasible	VU	(0.35, 0.65, 0.80)
Very Very Unfeasible	VVU	(0.25, 0.45, 0.90)
Extremely Unfeasible	EU	(0.15, 0.35, 0.95)

Step-2:Computing of the weights of Decision Makers–Table 13, lists the importance rankings that the president of NGO granted to each of the field specialists/Decision Makers $\varepsilon_t\,(t = 1, 2, 3, ..., h)$. EmployingEq.(13). it is possible to determine each expert's own weight.

Table 13: Assigning and computing of Weights of Expert (DM)

DMs	Ling. Var.	PNNs	Weights (ℓ_t)
ε_1	FH	(0.64, 0.42, 0.37)	0.2430
ε_2	VH	(0.92, 0.25, 0.11)	0.2832
ε_3	H	(0.78, 0.35, 0.24)	0.2832
ε_4	M	(0.50, 0.55, 0.50)	0.2077

Step-3:Assigning of the Decision Makers Judgements-The language expressions/ linguistic terms used in table 14 to describe the individual viewpoints of each Decision Makers on the decision-making panel with regard to each alternative and all taken-into-account criteria. The Pythagorean Neutrosophic decision matrix

[PNDM] $M^{(1)}, M^{(2)}, M^{(3)}$ and $M^{(4)}$ that highlight the unique opinions of the DM $\varepsilon_1, \varepsilon_2, \varepsilon_3$ and ε_4 are shown in tables 15-18, respectively.

Table 14: Judgement of Decision Expert in linguistic variables

		χ_1	χ_2	χ_3	χ_4	χ_5	χ_6	χ_7	χ_8
ε_1	Λ_1	MU	VVF	MU	VF	U	F	MF	MF
	Λ_2	VVU	EU	MU	M	EU	U	MF	F
	Λ_3	VU	M	VF	MF	MU	VF	EU	VF
	Λ_4	MF	M	F	EF	VVF	U	MU	F
	Λ_5	M	VF	VVF	MU	VU	EU	M	MU
	Λ_6	F	MF	M	MU	VF	EF	U	VU
	Λ_7	VVU	MU	MU	MU	VVF	F	F	F
ε_2	Λ_1	VF	M	MU	U	VU	M	VU	M
	Λ_2	F	VF	VVF	VF	F	VF	VF	F
	Λ_3	M	MU	MU	U	U	MF	MF	VU
	Λ_4	F	VF	VVF	VVF	EF	EF	VF	M
	Λ_5	M	MF	MU	MU	M	M	U	MU
	Λ_6	VF	VF	F	MU	M	MU	MF	VU
	Λ_7	U	MF	M	MU	MU	F	F	F
ε_3	Λ_1	MU	U	U	VU	VU	VVU	EU	VU
	Λ_2	MU	M	MU	EU	VVU	M	MU	MF
	Λ_3	F	F	MF	M	MF	MU	VU	VU
	Λ_4	EF	VF	VVF	MF	MF	M	M	M
	Λ_5	MU	U	MF	VU	VVU	EU	F	F
	Λ_6	VVF	F	MF	M	MU	U	U	U
	Λ_7	VU	VU	U	M	MU	MU	U	U
ε_4	Λ_1	MF	MU	U	VU	VVU	VU	VU	F
	Λ_2	M	MF	MU	U	VU	MF	U	U
	Λ_3	MF	M	MU	VU	VVU	EU	U	VF
	Λ_4	VVF	EF	VF	VF	F	EF	MF	MF
	Λ_5	M	MU	MU	M	VU	VU	VVU	EU
	Λ_6	M	MF	MF	F	F	U	VU	VVU
	Λ_7	VVU	VU	U	MF	M	U	MF	VF

Table 15: Judgement of Decision Expert ε_1 in linguistic variables

$M^{(1)}$	χ_1	χ_2	χ_3	χ_4	χ_5	χ_6	χ_7	χ_8
Λ_1	(0.45, 0.90, 0.55)	(0.95, 0.35, 0.15)	(0.45, 0.90, 0.55)	(0.90, 0.42, 0.25)	(0.40, 0.55, 0.70)	(0.80, 0.55, 0.35)	(0.70, 0.74, 0.40)	(0.70, 0.74, 0.40)
Λ_2	(0.25, 0.45, 0.90)	(0.15, 0.35, 0.95)	(0.45, 0.90, 0.55)	(0.55, 0.85, 0.45)	(0.15, 0.35, 0.95)	(0.40, 0.55, 0.70)	(0.70, 0.74, 0.40)	(0.80, 0.55, 0.35)
Λ_3	(0.35, 0.65, 0.80)	(0.55, 0.85, 0.45)	(0.90, 0.42, 0.25)	(0.70, 0.74, 0.40)	(0.45, 0.90, 0.55)	(0.90, 0.42, 0.25)	(0.15, 0.35, 0.95)	(0.90, 0.42, 0.25)
Λ_4	(0.70, 0.74, 0.40)	(0.55, 0.85, 0.45)	(0.80, 0.55, 0.35)	(0.99, 0.05, 0.01)	(0.95, 0.35, 0.15)	(0.40, 0.55, 0.70)	(0.45, 0.90, 0.55)	(0.80, 0.55, 0.35)
Λ_5	(0.55, 0.85, 0.45)	(0.90, 0.42, 0.25)	(0.95, 0.35, 0.15)	(0.45, 0.90, 0.55)	(0.35, 0.65, 0.80)	(0.15, 0.35, 0.95)	(0.55, 0.85, 0.45)	(0.45, 0.90, 0.55)
Λ_6	(0.80, 0.55, 0.35)	(0.70, 0.74, 0.40)	(0.55, 0.85, 0.45)	(0.45, 0.90, 0.55)	(0.90, 0.42, 0.25)	(0.99, 0.05, 0.01)	(0.40, 0.55, 0.70)	(0.35, 0.65, 0.80)
Λ_7	(0.25, 0.45, 0.90)	(0.45, 0.90, 0.55)	(0.45, 0.90, 0.55)	(0.45, 0.90, 0.55)	(0.95, 0.35, 0.15)	(0.80, 0.55, 0.35)	(0.80, 0.55, 0.35)	(0.80, 0.55, 0.35)

Table 16: Judgement of Decision Expert ε_2 in linguistic variables

$M^{(2)}$	χ_1	χ_2	χ_3	χ_4	χ_5	χ_6	χ_7	χ_8
Λ_1	(0.90, 0.42, 0.25)	(0.55, 0.85, 0.45)	(0.45, 0.90, 0.55)	(0.40, 0.55, 0.70)	(0.35, 0.65, 0.80)	(0.55, 0.85, 0.45)	(0.35, 0.65, 0.80)	(0.55, 0.85, 0.45)
Λ_2	(0.80, 0.55, 0.35)	(0.90, 0.42, 0.25)	(0.95, 0.35, 0.15)	(0.90, 0.42, 0.25)	(0.80, 0.55, 0.35)	(0.90, 0.42, 0.25)	(0.90, 0.42, 0.25)	(0.80, 0.55, 0.35)
Λ_3	(0.55, 0.85, 0.45)	(0.45, 0.90, 0.55)	(0.45, 0.90, 0.55)	(0.40, 0.55, 0.70)	(0.40, 0.55, 0.70)	(0.70, 0.74, 0.40)	(0.70, 0.74, 0.40)	(0.35, 0.65, 0.80)
Λ_4	(0.80, 0.55, 0.35)	(0.90, 0.42, 0.25)	(0.95, 0.35, 0.15)	(0.95, 0.35, 0.15)	(0.99, 0.05, 0.01)	(0.99, 0.05, 0.01)	(0.90, 0.42, 0.25)	(0.55, 0.85, 0.45)
Λ_5	(0.55, 0.85, 0.45)	(0.70, 0.74, 0.40)	(0.45, 0.90, 0.55)	(0.45, 0.90, 0.55)	(0.55, 0.85, 0.45)	(0.55, 0.85, 0.45)	(0.40, 0.55, 0.70)	(0.45, 0.90, 0.55)
Λ_6	(0.90, 0.42, 0.25)	(0.90, 0.42, 0.25)	(0.80, 0.55, 0.35)	(0.45, 0.90, 0.55)	(0.55, 0.85, 0.45)	(0.45, 0.90, 0.55)	(0.70, 0.74, 0.40)	(0.35, 0.65, 0.80)
Λ_7	(0.40, 0.55, 0.70)	(0.70, 0.74, 0.40)	(0.55, 0.85, 0.45)	(0.45, 0.90, 0.55)	(0.45, 0.90, 0.55)	(0.80, 0.55, 0.35)	(0.80, 0.55, 0.35)	(0.80, 0.55, 0.35)

Table 17: Judgement of Decision Expert ε_3 in linguistic variables

$M^{(3)}$	χ_1	χ_2	χ_3	χ_4	χ_5	χ_6	χ_7	χ_8
Λ_1	(0.45, 0.90, 0.55)	(0.40, 0.55, 0.70)	(0.40, 0.55, 0.70)	(0.35, 0.65, 0.80)	(0.35, 0.65, 0.80)	(0.25, 0.45, 0.90)	(0.15, 0.35, 0.95)	(0.35, 0.65, 0.80)
Λ_2	(0.45, 0.90, 0.55)	(0.55, 0.85, 0.45)	(0.45, 0.90, 0.55)	(0.15, 0.35, 0.95)	(0.25, 0.45, 0.90)	(0.55, 0.85, 0.45)	(0.45, 0.90, 0.55)	(0.70, 0.74, 0.40)
Λ_3	(0.80, 0.55, 0.35)	(0.80, 0.55, 0.35)	(0.70, 0.74, 0.40)	(0.55, 0.85, 0.45)	(0.70, 0.74, 0.40)	(0.45, 0.90, 0.55)	(0.35, 0.65, 0.80)	(0.35, 0.65, 0.80)
Λ_4	(0.99, 0.05, 0.01)	(0.90, 0.42, 0.25)	(0.95, 0.35, 0.15)	(0.70, 0.74, 0.40)	(0.70, 0.74, 0.40)	(0.55, 0.85, 0.45)	(0.55, 0.85, 0.45)	(0.55, 0.85, 0.45)
Λ_5	(0.45, 0.90, 0.55)	(0.40, 0.55, 0.70)	(0.70, 0.74, 0.40)	(0.35, 0.65, 0.80)	(0.25, 0.45, 0.90)	(0.15, 0.35, 0.95)	(0.80, 0.55, 0.35)	(0.80, 0.55, 0.35)
Λ_6	(0.95, 0.35, 0.15)	(0.80, 0.55, 0.35)	(0.70, 0.74, 0.40)	(0.55, 0.85, 0.45)	(0.45, 0.90, 0.55)	(0.40, 0.55, 0.70)	(0.40, 0.55, 0.70)	(0.40, 0.55, 0.70)
Λ_7	(0.35, 0.65, 0.80)	(0.35, 0.65, 0.80)	(0.40, 0.55, 0.70)	(0.55, 0.85, 0.45)	(0.45, 0.90, 0.55)	(0.45, 0.90, 0.55)	(0.40, 0.55, 0.70)	(0.40, 0.55, 0.70)

Table 18: Judgement of Decision Expert ε_4 in linguistic variables

$M^{(4)}$	χ_1	χ_2	χ_3	χ_4	χ_5	χ_6	χ_7	χ_8
Λ_1	(0.70, 0.74, 0.40)	(0.45, 0.90, 0.55)	(0.40, 0.55, 0.70)	(0.35, 0.65, 0.80)	(0.25, 0.45, 0.90)	(0.35, 0.65, 0.80)	(0.35, 0.65, 0.80)	(0.80, 0.55, 0.35)
Λ_2	(0.55, 0.85, 0.45)	(0.70, 0.74, 0.40)	(0.45, 0.90, 0.55)	(0.40, 0.55, 0.70)	(0.35, 0.65, 0.80)	(0.70, 0.74, 0.40)	(0.40, 0.55, 0.70)	(0.40, 0.55, 0.70)
Λ_3	(0.70, 0.74, 0.40)	(0.55, 0.85, 0.45)	(0.45, 0.90, 0.55)	(0.35, 0.65, 0.80)	(0.25, 0.45, 0.90)	(0.15, 0.35, 0.95)	(0.40, 0.55, 0.70)	(0.90, 0.42, 0.25)
Λ_4	(0.95, 0.35, 0.15)	(0.99, 0.05, 0.01)	(0.90, 0.42, 0.25)	(0.90, 0.42, 0.25)	(0.80, 0.55, 0.35)	(0.99, 0.05, 0.01)	(0.70, 0.74, 0.40)	(0.70, 0.74, 0.40)
Λ_5	(0.55, 0.85, 0.45)	(0.45, 0.90, 0.55)	(0.45, 0.90, 0.55)	(0.55, 0.85, 0.45)	(0.35, 0.65, 0.80)	(0.35, 0.65, 0.80)	(0.25, 0.45, 0.90)	(0.15, 0.35, 0.95)
Λ_6	(0.55, 0.85, 0.45)	(0.70, 0.74, 0.40)	(0.70, 0.74, 0.40)	(0.80, 0.55, 0.35)	(0.80, 0.55, 0.35)	(0.40, 0.55, 0.70)	(0.35, 0.65, 0.80)	(0.25, 0.45, 0.90)
Λ_7	(0.25, 0.45, 0.90)	(0.35, 0.65, 0.80)	(0.40, 0.55, 0.70)	(0.70, 0.74, 0.40)	(0.55, 0.85, 0.45)	(0.40, 0.55, 0.70)	(0.70, 0.74, 0.40)	(0.90, 0.42, 0.25)

Step-4*:Aggregation of the Decision Makers Judgements*-According to the PNWA operator and the decision-making experts' normalised weights, the individual judgements of each decision maker are combined. Table 19 contains the combined Pythagorean Neutrosophic decision matrix $\ddot{M} = \left(\ddot{M}_{ab}\right)_{7\times8}$.

Table 19: Aggregated PNDM

$\ddot{M}$	χ_1	χ_2	χ_3	χ_4	χ_5	χ_6	χ_7	χ_8
Λ_1	(0.7182, 0.6964, 0.4118)	(0.7300, 0.6175, 0.404)	(0.4274, 0.7127, 0.6166)	(0.6344, 0.5575, 0.5807)	(0.3461, 0.5782, 0.7936)	(0.5710, 0.6106, 0.5737)	(0.4566, 0.5689, 0.7076)	(0.6333, 0.6991, 0.4837)
Λ_2	(0.5967, 0.6537, 0.5232)	(0.7135, 0.5452, 0.4458)	(0.7485, 0.6888, 0.3807)	(0.6718, 0.5022, 0.5095)	(0.5363, 0.4837, 0.6810)	(0.7259, 0.6085, 0.4139)	(0.7199, 0.6243, 0.4281)	(0.7274, 0.5952, 0.4188)
Λ_3	(0.6484, 0.6891, 0.4724)	(0.6265, 0.7694, 0.4455)	(0.7073, 0.7099, 0.4172)	(0.5342, 0.6872, 0.5585)	(0.5069, 0.6435, 0.5993)	(0.6948, 0.5815, 0.4648)	(0.4842, 0.5604, 0.6667)	(0.7481, 0.5339, 0.4736)
Λ_4	(0.9283, 0.2843, 0.1177)	(0.9148, 0.3204, 0.1478)	(0.9199, 0.4057, 0.2049)	(0.9390, 0.2765, 0.1121)	(0.9345, 0.2704, 0.1078)	(0.9342, 0.1903, 0.0773)	(0.7299, 0.6859, 0.3904)	(0.6659, 0.7430, 0.4131)
Λ_5	(0.5265, 0.863, 0.4747)	(0.7052, 0.6206, 0.4424)	(0.7584, 0.6791, 0.3685)	(0.4521, 0.8156, 0.5829)	(0.4039, 0.6359, 0.7014)	(0.3623, 0.5117, 0.7419)	(0.5868, 0.5864, 0.5509)	(0.5716, 0.6488, 0.5463)
Λ_6	(0.8698, 0.4946, 0.2676)	(0.8053, 0.5825, 0.3379)	(0.7081, 0.7037, 0.3963)	(0.5896, 0.8002, 0.4747)	(0.7353, 0.6643, 0.3906)	(0.8165, 0.3531, 0.2329)	(0.5139, 0.6193, 0.6142)	(0.3473, 0.5760, 0.7912)
Λ_7	(0.3272, 0.5253, 0.8123)	(0.5146, 0.7298, 0.6002)	(0.4616, 0.7013, 0.5825)	(0.5465, 0.8511, 0.4880)	(0.7311, 0.7070, 0.3847)	(0.6852, 0.6270, 0.4559)	(0.7177, 0.5850, 0.4327)	(0.7778, 0.5200, 0.3925)

Step-5:*Normalization of Aggregated PNDM*- Let X_B and X_C represent the corresponding groups of criteria that are of the benefit-type(Positive) criteria $\chi_B = \{\chi_1, \chi_2, \chi_4, \chi_6, \chi_7\}$, cost type (Negative) criteria $\chi_C = \{\chi_3, \chi_5, \chi_8\}$. The aggregated PNDM, $\ddot{M} = \left(\ddot{M}_{ab}\right)_{7\times8}$, can be converted into the normalized aggregated PNDM, $M = \left(M_{ab}\right)_{7\times8}$ which displays the evaluation information of each alternative with respect to each benefit or cost criterion, in standard form, for additional calculations. Table 20 demonstrates how the matrix M is built andone can describe the PNN for M_{ab},

Table 20: Normalized Aggregated PNDM

M	χ_1	χ_2	χ_3	χ_4	χ_5	χ_6	χ_7	χ_8
Λ_1	(0.7182, 0.6964, 0.4118)	(0.7300, 0.6175, 0.404)	(0.6166, 0.7127, 0.4274)	(0.6344, 0.5575, 0.5807)	(0.7936, 0.5782, 0.3461)	(0.5710, 0.6106, 0.5737)	(0.4566, 0.5689, 0.7076)	(0.4837, 0.6991, 0.6333)
Λ_2	(0.5967, 0.6537, 0.5232)	(0.7135, 0.5452, 0.4458)	(0.3807, 0.6888, 0.7485)	(0.6718, 0.5022, 0.5095)	(0.6810, 0.4837, 0.5363)	(0.7259, 0.6085, 0.4139)	(0.7199, 0.6243, 0.4281)	(0.4188, 0.5952, 0.7274)
Λ_3	(0.6484, 0.6891, 0.4724)	(0.6265, 0.7694, 0.4455)	(0.4172, 0.7099, 0.7073)	(0.5342, 0.6872, 0.5585)	(0.5993, 0.6435, 0.5069)	(0.6948, 0.5815, 0.4648)	(0.4842, 0.5604, 0.6667)	(0.4736, 0.5339, 0.7481)
Λ_4	(0.9283, 0.2843, 0.1177)	(0.9148, 0.3204, 0.1478)	(0.2049, 0.4057, 0.9199)	(0.9390, 0.2765, 0.1121)	(0.1078, 0.2704, 0.9345)	(0.9342, 0.1903, 0.0773)	(0.7299, 0.6859, 0.3904)	(0.4131, 0.7430, 0.6659)
Λ_5	(0.5265, 0.863, 0.4747)	(0.7052, 0.6206, 0.4424)	(0.3685, 0.6791, 0.7584)	(0.4521, 0.8156, 0.5829)	(0.7014, 0.6359, 0.4039)	(0.3623, 0.5117, 0.7419)	(0.5868, 0.5864, 0.5509)	(0.5463, 0.6488, 0.5716)
Λ_6	(0.8698, 0.4946, 0.2676)	(0.8053, 0.5825, 0.3379)	(0.3963, 0.7037, 0.7081)	(0.5896, 0.8002, 0.4747)	(0.3906, 0.6643, 0.7353)	(0.8165, 0.3531, 0.2329)	(0.5139, 0.6193, 0.6142)	(0.7912, 0.5760, 0.3473)
Λ_7	(0.3272, 0.5253, 0.8123)	(0.5146, 0.7298, 0.6002)	(0.5825, 0.7013, 0.4616)	(0.5465, 0.8511, 0.4880)	(0.3847, 0.7070, 0.7311)	(0.6852, 0.6270, 0.4559)	(0.7177, 0.5850, 0.4327)	(0.3925, 0.5200, 0.7778)

Step-6*:Erection of weight matrix of criteria*-The decision-making panel's linguistic labels for each criterion, PN-weights, and normalised weights of the criteria are shown in table 21.

Table 21: Linguistic Variables to Unfold Importance of Criteria

Criteria → *Expert* ↓	χ_1	χ_2	χ_3	χ_4	χ_5	χ_6	χ_7	χ_8
ε_1	VH (0.92, 0.25, 0.11)	VH (0.92, 0.25, 0.11)	M (0.50, 0.55, 0.50)	FH (0.64, 0.42, 0.37)	M (0.50, 0.55, 0.50)	VL (0.08, 0.90, 0.89)	M (0.50, 0.55, 0.50)	FH (0.64, 0.42, 0.37)
ε_2	H (0.78, 0.35, 0.24)	VH (0.92, 0.25, 0.11)	L (0.22, 0.85, 0.76)	M (0.50, 0.55, 0.50)	H (0.78, 0.35, 0.24)	FH (0.64, 0.42, 0.37)	VH (0.92, 0.25, 0.11)	L (0.22, 0.85, 0.76)
ε_3	M (0.50, 0.55, 0.50)	H (0.78, 0.35, 0.24)	FH (0.64, 0.42, 0.37)	VH (0.92, 0.25, 0.11)	H (0.78, 0.35, 0.24)	FL (0.36, 0.74, 0.63)	FH (0.64, 0.42, 0.37)	M (0.50, 0.55, 0.50)
ε_4	FH (0.64, 0.42, 0.37)	VH (0.92, 0.25, 0.11)	H (0.78, 0.35, 0.24)	FL (0.36, 0.74, 0.63)	VL (0.08, 0.90, 0.89)	M (0.50, 0.55, 0.50)	L (0.22, 0.85, 0.76)	VL (0.08, 0.90, 0.89)

$$W_{\{\chi_1,\chi_2,\chi_3,\chi_4,\chi_5,\chi_6,\chi_7,\chi_8\}} = \begin{pmatrix} (0.7721, 0.3778, 0.2641) \\ (0.8961, 0.2734, 0.1354) \\ (0.5850, 0.5272, 0.4461) \\ (0.7221, 0.4442, 0.3259) \\ (0.6660, 0.4753, 0.3766) \\ (0.4682, 0.6215, 0.5617) \\ (0.7267, 0.4482, 0.3279) \\ (0.4444, 0.6455, 0.5898) \end{pmatrix}^T$$

And

$$\begin{aligned} w(\chi_1) &= 0.1375 \\ w(\chi_2) &= 0.1449 \\ w(\chi_3) &= 0.1187 \\ w(\chi_4) &= 0.1338 \\ w(\chi_5) &= 0.1283 \\ w(\chi_6) &= 0.1028 \\ w(\chi_7) &= 0.1347 \\ w(\chi_8) &= 0.0992 \end{aligned}$$

Step-7: *Construction of Weighted normalized aggregation PNDM*-The weighted normalized aggregated PNDM, $\hat{M} = \left(\hat{M}_{ab}\right)_{f \times g}$ is created as shown in table 22 in the order of integrating the data from the normalized aggregated PNDM and the criteria weight matrix $\hat{M}_{ab} = \left(\phi_{\hat{M}_a}(\chi_b), \varphi_{\hat{M}_a}(\chi_b), \gamma_{\hat{M}_a}(\chi_b)\right)$ may be generated by using the multiplication operator, which is specified in Eq(19).

Table 22: Weighted Normalized Aggregated PNDM

$\hat{M}$	χ_1	χ_2	χ_3	χ_4	χ_5	χ_6	χ_7	χ_8
Λ_1	(0.5545, 0.7473, 0.4770)	(0.6542, 0.6539, 0.4226)	(0.3607, 0.8029, 0.5876)	(0.4581, 0.6684, 0.6384)	(0.5285, 0.6962, 0.4946)	(0.2673, 0.7843, 0.7354)	(0.3318, 0.6779, 0.7446)	(0.2150, 0.8377, 0.7807)
Λ_2	(0.4607, 0.7135, 0.5696)	(0.6394, 0.5914, 0.4620)	(0.2227, 0.7877, 0.8048)	(0.4851, 0.6323, 0.5816)	(0.4535, 0.6380, 0.6234)	(0.3399, 0.7833, 0.6579)	(0.5232, 0.7158, 0.5207)	(0.1861, 0.7895, 0.8324)
Λ_3	(0.5006, 0.7415, 0.5266)	(0.5614, 0.7890, 0.4617)	(0.2441, 0.8011, 0.7744)	(0.3857, 0.7592, 0.6205)	(0.3991, 0.7392, 0.6019)	(0.3253, 0.7706, 0.6807)	(0.3519, 0.6722, 0.7101)	(0.2105, 0.7635, 0.8443)
Λ_4	(0.7167, 0.4605, 0.2875)	(0.8198, 0.4120, 0.1994)	(0.1199, 0.6299, 0.9364)	(0.6781, 0.5086, 0.3427)	(0.0718, 0.5315, 0.9441)	(0.4374, 0.6391, 0.5653)	(0.5304, 0.7595, 0.4935)	(0.1836, 0.8595, 0.7981)
Λ_5	(0.4065, 0.8839, 0.5286)	(0.6319, 0.6566, 0.4588)	(0.2156, 0.7816, 0.8122)	(0.3265, 0.8551, 0.6402)	(0.4671, 0.7341, 0.5309)	(0.1696, 0.7396, 0.8320)	(0.4264, 0.6897, 0.6151)	(0.2428, 0.8138, 0.7490)
Λ_6	(0.6716, 0.5937, 0.3693)	(0.7216, 0.6235, 0.3611)	(0.2318, 0.7972, 0.7750)	(0.4258, 0.8434, 0.5546)	(0.2601, 0.7533, 0.7783)	(0.3823, 0.6803, 0.5938)	(0.3735, 0.7123, 0.6665)	(0.3516, 0.7812, 0.6531)
Λ_7	(0.2526, 0.6159, 0.8268)	(0.4611, 0.7534, 0.6099)	(0.3408, 0.7957, 0.6080)	(0.3946, 0.8825, 0.5649)	(0.2562, 0.7828, 0.7749)	(0.3208, 0.7922, 0.6766)	(0.5216, 0.6887, 0.5240)	(0.1744, 0.7579, 0.8616)

Step-8: *Computation of Score degrees with respect to WNA-PNDM*- table 23 contains the computed score values of corresponding PNNs in the weighted normalized aggregated PNDM $\hat{M}$.

Table 23: Score Value of Weighted Normalized Aggregated PNDM

P	χ_1	χ_2	χ_3	χ_4	χ_5	χ_6	χ_7	χ_8
Λ_1	−0.4785	−0.1782	−0.8598	−0.6445	−0.4500	−1.0845	−0.9039	−1.2650
Λ_2	−0.6213	−0.1544	−1.2186	−0.5027	−0.5900	−0.9309	−0.5098	−1.2816
Λ_3	−0.5765	−0.5205	−1.1819	−0.8126	−0.7494	−0.9514	−0.8323	−1.2515
Λ_4	0.2189	0.4626	−1.2592	0.0837	−1.1687	−0.5367	−0.5391	−1.3420
Λ_5	−0.8955	−0.2423	−1.2241	−1.0344	−0.6026	−1.2105	−0.6722	−1.1643
Λ_6	−0.0378	0.0016	−1.1824	−0.8376	−1.1056	−0.6693	−0.8121	−0.9132
Λ_7	−0.9991	−0.7270	−0.8867	−0.9422	−1.1476	−0.9825	−0.4768	−1.2864

5.3.2 Phase II: Pythagorean Neutrosophic Ranking Phase (PN-ELECTRE III)

5.3.2.1Module-I: The construction of outranking relations

Step-9. *Establishmentof Threshold Functions*- For each criteria χ_b, Here are preference threshold values $p(\chi_b)$ and indifference threshold values $q(\chi_b)$ and veto threshold values $v(\chi_b)$ as shown in table 24,

Table 24: Assigning of PNN's Threshold functions and its Score Values

Criteria → Threshold Values ↓	χ_1	χ_2	χ_3	χ_4	χ_5	χ_6	χ_7	χ_8
	F	EF	MF	VF	M	U	VVF	MU
$q(\chi_j)$	(0.80, 0.55, 0.35)	(0.99, 0.05, 0.01)	(0.70, 0.74, 0.40)	(0.90, 0.42, 0.25)	(0.55, 0.85, 0.45)	(0.40, 0.55, 0.70)	(0.95, 0.35, 0.15)	(0.45, 0.90, 0.55)
$s\left(q(\chi_j)\right)$	0.2150	0.9775	−0.2176	0.5711	−0.6225	−0.6325	0.7575	−0.9100
	MU	M	M	F	MF	VU	MF	M
$p(\chi_j)$	(0.45, 0.90, 0.55)	(0.55, 0.85, 0.45)	(0.55, 0.85, 0.45)	(0.80, 0.55, 0.35)	(0.70, 0.74, 0.40)	(0.35, 0.65, 0.80)	(0.70, 0.74, 0.40)	(0.55, 0.85, 0.45)
$s\left(p(\chi_j)\right)$	−0.9100	−0.6225	−0.6225	0.2150	−0.2176	−0.9400	−0.2176	−0.6225
	EF	MF	VF	M	MU	M	M	MF
$v(\chi_j)$	(0.99, 0.05, 0.01)	(0.70, 0.74, 0.40)	(0.90, 0.42, 0.25)	(0.55, 0.85, 0.45)	(0.45, 0.90, 0.55)	(0.55, 0.85, 0.45)	(0.55, 0.85, 0.45)	(0.70, 0.74, 0.40)
$s\left(v(\chi_j)\right)$	0.9775	−0.2176	0.5711	−0.6225	−0.6700	−0.6225	−0.6225	−0.2176

Step-10. *Calculation of difference in the score degrees*- The differences in the score values/degrees of the feasibility of every pair of alternatives are ccomputing of

$$\lambda_{ij}^{b} = s\left(\chi_b(\lambda_j)\right) - s\left(\chi_b(\lambda_i)\right)\ \forall i, j = 1,2,3,...,7, i \neq j$$

, where b= 1,2,….8, in tables 25-28 as follows:

λ_{ij}^{1} w.r.t. χ_1, $\forall i, j = 1,2,3,...,7, i \neq j$ Table 25

—	−0.1428	−0.098	0.6974	−0.417	0.4407	−0.5206
0.1428	—	0.0448	0.8402	−0.2742	0.5835	−0.3778
0.098	−0.0448	—	0.7954	−0.319	0.5387	−0.4226
−0.6974	−0.8402	−0.7954	—	−1.1144	−0.2567	−1.218
0.417	0.2742	0.319	1.1144	—	0.8577	−0.1036
−0.4407	−0.5835	−0.5387	0.2567	−0.8577	—	−0.9613
0.5206	0.3778	0.4226	1.218	0.1036	0.9613	—

λ_{ij}^{2} w.r.t. χ_2, $\forall i, j = 1,2,3,...,7, i \neq j$

—	0.0238	−0.3423	0.6408	−0.0641	0.1798	−0.5488
−0.0238	—	−0.3661	0.617	−0.0879	0.156	−0.5726
0.3423	0.3661	—	0.9831	0.2782	0.5221	−0.2065
−0.6408	−0.617	−0.9831	—	−0.7049	−0.461	−1.1896
0.0641	0.0879	−0.2782	0.7049	—	0.2439	−0.4847
−0.1798	−0.156	−0.5221	0.461	−0.2439	—	−0.7286
0.5488	0.5726	0.2065	1.1896	0.4847	0.7286	—

λ_{ij}^{3} w.r.t. χ_3, $\forall i, j = 1,2,3,...,7, i \neq j$ Table 26

—	−0.3588	−0.3221	−0.3994	−0.3643	−0.3226	−0.0269
0.3588	—	0.0367	−0.0406	−0.0055	0.0362	0.3319
0.3221	−0.0367	—	−0.0773	−0.0422	−0.0005	0.2952
0.3994	0.0406	0.0773	—	0.0351	0.0768	0.3725
0.3643	0.0055	0.0422	−0.0351	—	0.0417	0.3374
0.3226	−0.0362	0.0005	−0.0768	−0.0417	—	0.2957
0.0269	−0.3319	−0.2952	−0.3725	−0.3374	−0.2957	—

λ_{ij}^{4} w.r.t. χ_4, $\forall i, j = 1,2,3,...,7, i \neq j$

—	0.1418	−0.1681	0.7282	−0.3899	−0.1931	−0.2977
−0.1418	—	−0.3099	0.5864	−0.5317	−0.3349	−0.4395
0.1681	0.3099	—	0.8963	−0.2218	−0.025	−0.1296
−0.7282	−0.5864	−0.8963	—	−1.1181	−0.9213	−1.0259
0.3899	0.5317	0.2218	1.1181	—	0.1968	0.0922
0.1931	0.3349	0.025	0.9213	−0.1968	—	−0.1046
0.2977	0.4395	0.1296	1.0259	−0.0922	0.1046	—

λ_{ij}^{5} w.r.t. χ_5, $\forall i, j = 1,2,3,...,7, i \neq j$ Table 27

—	−0.14	−0.2994	−0.7187	−0.1526	−0.6556	−0.6976
0.14	—	−0.1594	−0.5787	−0.0126	−0.5156	−0.5576
0.2994	0.1594	—	−0.4193	0.1468	−0.3562	−0.3982
0.7187	0.5787	0.4193	—	0.5661	0.0631	0.0211
0.1526	0.0126	−0.1468	−0.5661	—	−0.503	−0.545
0.6556	0.5156	0.3562	−0.0631	0.503	—	−0.042
0.6976	0.5576	0.3982	−0.0211	0.545	0.042	—

λ_{ij}^{6} w.r.t. χ_6, $\forall i, j = 1,2,3,...,7, i \neq j$

—	0.1536	0.1331	0.5478	−0.126	0.4152	0.102
−0.1536	—	−0.0205	0.3942	−0.2796	0.2616	−0.0516
−0.1331	0.0205	—	0.4147	−0.2591	0.2821	−0.0311
−0.5478	−0.3942	−0.4147	—	−0.6738	−0.1326	−0.4458
0.126	0.2796	0.2591	0.6738	—	0.5412	0.228
−0.4152	−0.2616	−0.2821	0.1326	−0.5412	—	−0.3132
−0.102	0.0516	0.0311	0.4458	−0.228	0.3132	—

λ_{ij}^{7} w.r.t. χ_7, $\forall i, j = 1,2,3,...,7, i \neq j$ Table 28

—	0.3941	0.0716	0.3648	0.2317	0.0918	0.4271
−0.3941	—	−0.3225	−0.0293	−0.1624	−0.3023	0.033
−0.0716	0.3225	—	0.2932	0.1601	0.0202	0.3555
−0.3648	0.0293	−0.2932	—	−0.1331	−0.273	0.0623
−0.2317	0.1624	−0.1601	0.1331	—	−0.1399	0.1954
−0.0918	0.3023	−0.0202	0.273	0.1399	—	0.3353
−0.4271	−0.033	−0.3555	−0.0623	−0.1954	−0.3353	—

λ_{ij}^{8} w.r.t. χ_8, $\forall i, j = 1,2,3,...,7, i \neq j$

—	−0.0166	0.0135	−0.077	0.1007	0.3518	−0.0214
0.0166	—	0.0301	−0.0604	0.1173	0.3684	−0.0048
−0.0135	−0.0301	—	−0.0905	0.0872	0.3383	−0.0349
0.077	0.0604	0.0905	—	0.1777	0.4288	0.0556
−0.1007	−0.1173	−0.0872	−0.1777	—	0.2511	−0.1221
−0.3518	−0.3684	−0.3383	−0.4288	−0.2511	—	−0.3732
0.0214	0.0048	0.0349	−0.0556	0.1221	0.3732	—

Step-11:*Calculation of Partial Concordance Indices and Concordance Matrix*-The partial concordance matrices shown in tables 29-32 as follows:

Table 29

Δ_1	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
λ_1	—	0	0	0	0	0	0
λ_2	0	—	0	0	0	0	0
λ_3	0	0	—	0	0	0	0
λ_4	0.2287	0.6647	0.5279	—	1	0	1
λ_5	0	0	0	0	—	0	0
λ_6	0	0	0	0	0.7182	—	1
λ_7	0	0	0	0	0	0	—

Δ_2	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
λ_1	—	0	0.1726	0	0	0	0.4585
λ_2	0	—	0.2056	0	0	0	0.4914
λ_3	0	0	—	0	0	0	0
λ_4	0.5858	0.5529	1	—	0.6746	0.3369	1
λ_5	0	0	0.0839	0	—	0	0.3697
λ_6	0	0	0.4215	0	0.0364	—	0.7074
λ_7	0	0	0	0	0	0	—

Table 30

Δ_3	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
λ_1	—	1	1	1	1	1	0.5592
λ_2	0	—	0.4122	0.5908	0.5097	0.4133	0
λ_3	0	0.5818	—	0.6757	0.5945	0.4982	0
λ_4	0	0.4031	0.3183	—	0.4159	0.3195	0
λ_5	0	0.4843	0.3994	0.5781	—	0.4006	0
λ_6	0	0.5807	0.4958	0.6745	0.5934	—	0
λ_7	0.4348	1	1	1	1	1	—

Δ_4	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
λ_1	—	0	0	0	0.2488	0	0.1157
λ_2	0	—	0.1333	0	0.4536	0.1694	0.3205
λ_3	0	0	—	0	0.0061	0	0
λ_4	0.7374	0.5326	0.9802	—	1	1	1
λ_5	0	0	0	0	—	0	0
λ_6	0	0	0	0	0	—	0
λ_7	0	0	0	0	0	0	—

Tables 31

Δ_5	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
λ_1	—	0.9016	1	1	0.9176	1	1
λ_2	0.5466	—	0.9262	1	0.7401	1	1
λ_3	0.3445	0.522	—	1	0.538	1	1
λ_4	0	0	0.1925	—	0.0063	0.6441	0.6974
λ_5	0.5306	0.7081	0.9102	1	—	1	1
λ_6	0	0.0704	0.2725	0.8041	0.0863	—	0.7774
λ_7	0	0.0171	0.2192	0.7509	0.0331	0.6709	—

Δ_6	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
λ_1	—	0.0733	0.0978	0	0.4072	0	0.1349
λ_2	0.4401	—	0.2812	0	0.5906	0	0.3183
λ_3	0.4156	0.2322	—	0	0.5661	0	0.2939
λ_4	0.9108	0.7274	0.7519	—	1	0.4150	0.789
λ_5	0.1063	0	0	0	—	0	0
λ_6	0.7525	0.5691	0.5936	0.0984	0.9029	—	0.6307
λ_7	0.3785	0.1951	0.2196	0	0.529	0	—

Tables 32

Δ_7	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
λ_1	—	0	0.1712	0	0	0.1471	0
λ_2	0.7273	—	0.6418	0.2917	0.4506	0.6177	0.2173
λ_3	0.3422	0	—	0	0.0656	0.2326	0
λ_4	0.6923	0.2217	0.6068	—	0.4156	0.5827	0.1823
λ_5	0.5334	0.0628	0.4479	0.0978	—	0.4238	0.0234
λ_6	0.3663	0	0.2808	0	0.0897	—	0
λ_7	0.7667	0.2961	0.6812	0.3311	0.49	0.6571	—

Δ_8	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
λ_1	—	0	0	0	0	0	0
λ_2	0	—	0	0	0	0	0
λ_3	0	0	—	0	0	0	0
λ_4	0	0	0	—	0	0	0
λ_5	0	0	0	0	—	0	0
λ_6	0.1710	0.1921	0.1538	0.2691	0.0427	—	0.1982
λ_7	0	0	0	0	0	0	—

Table 33: Comprehensive Concordance matrix Δ

Δ	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
λ_1	—	0.2419	0.3051	0.247	0.3116	0.2668	0.2905
λ_2	0.2133	—	0.3307	0.2377	0.3376	0.2832	0.3044
λ_3	0.133	0.1599	—	0.2085	0.2074	0.2188	0.1585
λ_4	0.4019	0.3953	0.5701	—	0.578	0.4243	0.6113
λ_5	0.1509	0.1568	0.2367	0.2101	—	0.2329	0.185
λ_6	0.1437	0.1555	0.269	0.22	0.2947	—	0.4242
λ_7	0.1938	0.1808	0.2612	0.2596	0.2433	0.2933	—

***Step-12*:** Calculation of Discordance Matrix in tables 34-37.

Table 34

∇_1	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
λ_1	—	0.4019	0.4394	1	0.1722	0.8908	0.0854
λ_2	0.6412	—	0.5591	1	0.2918	1	0.205
λ_3	0.6036	0.484	—	1	0.2543	0.9729	0.1675
λ_4	0	0	0	—	0	0.3065	0
λ_5	0.8709	0.7513	0.7888	1	—	1	0.4347
λ_6	0.1523	0.0327	0.0702	0.7366	0	—	0
λ_7	0.9577	0.8381	0.8756	1	0.6083	1	—

∇_2	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
λ_1	—	0.2476	0	0.8803	0.1574	0.4075	0
λ_2	0.1987	—	0	0.8559	0.133	0.3831	0
λ_3	0.5742	0.5986	—	1	0.5085	0.7586	0.0114
λ_4	0	0	0	—	0	0	0
λ_5	0.2889	0.3133	0	0.9461	—	0.4733	0
λ_6	0.0388	0.0632	0	0.6959	0	—	0
λ_7	0.786	0.8104	0.4349	1	0.7202	0.9704	—

Table 35

∇_3	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
λ_1	—	0	0	0	0	0	0
λ_2	0.4038	—	0	0	0	0	0.3283
λ_3	0.3008	0	—	0	0	0	0.2252
λ_4	0.5178	0	0	—	0	0	0.4423
λ_5	0.4193	0	0	0	—	0	0.3437
λ_6	0.3022	0	0	0	0	—	0.2266
λ_7	0	0	0	0	0	0	—

∇_4	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
λ_1	—	0.4557	0.0628	1	0	0.0311	0
λ_2	0.0961	—	0	1	0	0	0
λ_3	0.489	0.6688	—	1	0	0.2442	0.1116
λ_4	0	0	0	—	0	0	0
λ_5	0.7703	0.95	0.5571	1	—	0.5254	0.3928
λ_6	0.5207	0.7005	0.3076	1	0.0264	—	0.1433
λ_7	0.6534	0.8331	0.4402	1	0.159	0.4085	—

Table 36

∇_5	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
λ_1	—	0	0	0	0	0	0
λ_2	0	—	0	0	0	0	0
λ_3	0	0	—	0	0	0	0
λ_4	0.3632	0.0187	0	—	0	0	0
λ_5	0	0	0	0	—	0	0
λ_6	0.2079	0	0	0	0	—	0
λ_7	0.3113	0	0	0	0	0	—

∇_6	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
λ_1	—	0	0	0.6135	0	0.3690	0
λ_2	0	—	0	0.3303	0	0.0859	0
λ_3	0	0	—	0.3681	0	0.1237	0
λ_4	0	0	0	—	0	0	0
λ_5	0	0.1191	0.0813	0.8457	—	0.6013	0.0240
λ_6	0	0	0	0	0	—	0
λ_7	0	0	0	0.4254	0	0.181	—

Table 37

∇_7	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	∇_8	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
λ_1	—	0.2349	0	0.1965	0.0219	0	0.2782	λ_1	—	0.2061	0.237	0.1442	0.3264	0.5839	0.2012
λ_2	0	—	0	0	0	0	0	λ_2	0.2402	—	0.254	0.1612	0.3435	0.601	0.2182
λ_3	0	0.141	—	0.1026	0	0	0.1843	λ_3	0.2093	0.1923	—	0.1303	0.3126	0.5701	0.1874
λ_4	0	0	0	—	0	0	0	λ_4	0.3021	0.2851	0.316	—	0.4054	0.6629	0.2802
λ_5	0	0	0	0	—	0	0	λ_5	0.1199	0.1029	0.1337	0.0409	—	0.4807	0.0979
λ_6	0	0.1145	0	0.0761	0	—	0.1578	λ_6	0	0	0	0	0	—	0
λ_7	0	0	0	0	0	0	—	λ_7	0.2451	0.2281	0.2589	0.1661	0.3484	0.6059	—

Step-13*:Calculation of Credibility Index-*

Table 38

μ	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
λ_1	—	0.136	0.2461	0	0.3049	0.0157	0.2905
λ_2	0.0712	—	0.2178	0	0.3346	0	0.2939
λ_3	0.0129	0.0178	—	0	0.1049	0.0012	0.1351
λ_4	0.324	0.3953	0.5701	—	0.578	0.2484	0.6113
λ_5	0.0036	0.0022	0.038	0	—	0	0.077
λ_6	0.06	0.0551	0.2548	0	0.2947	—	0.4242
λ_7	0.0009	0.0016	0.0255	0	0.0401	0	—

5.3.2.2 Module II: The Exploitation of Outranking Relations

Step-13*:Calculation of Credibility Index-Table Ranking of Alternatives*

Table 39

Alternatives	μ^+	μ^-	μ	Ranking
λ_1	0.9932	0.4726	0.5206	3
λ_2	0.9175	0.6080	0.3095	4
λ_3	0.2719	1.3523	−1.0804	5
λ_4	2.7271	0	2.7271	1
λ_5	0.1208	1.6572	−1.5364	6
λ_6	1.0888	0.2653	0.8235	2
λ_7	0.0681	1.8320	−1.7639	7

$$\lambda_4 \succ \lambda_6 \succ \lambda_1 \succ \lambda_2 \succ \lambda_3 \succ \lambda_5 \succ \lambda_7$$

$$\text{Jalaun} \succ \text{Lalitpur} \succ \text{Banda} \succ \text{Chitrakoot} \succ \text{Hamirpur} \succ \text{Jhansi} \succ \text{Mahoba}$$

Thus, District Jalaun is the best Location in Bundelkhand region of Uttar Pradesh for Solar Power Plant/Park installation.

6. Conclusion

In conclusion, the research paper titled "Two Phase Decision-Aiding System for solar plant location problem using ELECTRE III Method in Pythagorean Neutrosophic programming approach: A case study on Green Energy in India" presents a novel approach to solving the solar plant location problem in India. The use of the ELECTRE III method in the Pythagorean Neutrosophic programming approach is a significant contribution to the field of decision-making under uncertainty. The paper's two-phase decision-aiding system allows for a comprehensive evaluation of potential solar plant locations, taking into account multiple criteria and stakeholder preferences. The case study on Green Energy in India demonstrates the effectiveness of the proposed method in identifying the most suitable locations for solar plants, considering economic, social, and environmental factors.

Overall, the paper highlights the importance of using advanced decision-making tools to address complex problems in renewable energy development. The proposed method can serve as a valuable resource for policymakers, investors, and stakeholders involved in the planning and implementation of solar energy projects in India and other countries facing similar challenges.

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