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A Modified Novel Method for Solving the Uncertainty Linear Programming Problems Based on Triangular Neutrosophic Number

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Abstract. Generally, linear programming (LP) problem is the most extensively utilized technique for solving and optimizing real-world problems due to its simplicity and efficiency. However, to deal with the inaccurate data, the neutrosophic set theory comes into play, which creates a simulation of the human decision-making process by considering all parts of the choice (i.e., agree, not sure, and disagree). Keeping the benefits in mind, we proposed the neutrosophic LP models based on triangular neutrosophic numbers (TNN) and provided a method for solving them. Fuzzy LP problem can be converted into crips LP problem based on the defined ranking function. The provided technique has been demonstrated with numerical examples given by Abdelfattah. Finally, we found that, when compared to previous approaches, the suggested method is simpler, more efficient, and capable of solving all types of fuzzy LP models.

AMS Subject Classification 2020: 90C70; 90C05
Keywords and Phrases: Linear Programming Problem, Triangular Neutrosophic Number, Ranking Function, Nutrosophic Linear Programming Problem.

1 Introduction

One of the most extensively used optimizations approaches in real-world applications is linear programming and it is a type of mathematical programming that has a linear objective function and a set of linear equality and inequality constraints. However, in real world issues, data precision is largely misleading, which has an impact on the best solution to LP problems. With erroneous and ambiguous data, probability distributions failed to transact. Zadeh [30] in 1965 proposed fuzzy sets to deal with ambiguous and imprecise data. Zimmermann [31] in 1978 offered the first definition and solution of the fuzzy LP problem. Zimmermann [32] in 1987, divided the fuzzy LP problems into two groups: symmetric and non-symmetric problems. In symmetric fuzzy LP problems, the weights of objectives and constraints are equal, whereas in non-symmetric fuzzy LP problems, the weights of objectives and constraints are not equal. Leung [20] in 2013 divided fuzzy LP problems into different categories, these are

1. problems with crisp objective and fuzzy constraint.
2. problems with crisp constraint and fuzzy objective.

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3. problems with fuzzy objectives and fuzzy constraints.
4. challenges with robust programming.

Kumar et al. [19] provide a fuzzy LP problem with equality and inequality constraints. Several authors proposed several methods for solving fuzzy LP with inequality constraints, as well as first converting fuzzy LP problems to their equivalent crisp model and then getting the best fuzzy solution to the original scenario. A large number of authors have explored the various aspects of fuzzy LP problems and provided various solutions. Lotfi et al. [21] introduced the entire fuzzy LP difficulties. Some researchers have proposed a ranking function for converting fuzzy LP problems into crisp LP analogues, which can then be solved using standard approaches. Ebrahimnejad and Tavana [12] proposed a novel technique for tackling fuzzy LP problems based on symmetric trapezoidal fuzzy numbers.

However, because it solely examines the truthiness function, the fuzzy set does not effectively represent unclear and imprecise information. Then, by considering both the truth and falsity functions, Atanassov [6] in 1986 created the notion of the intuitionistic fuzzy set to handle unclear and imprecise information. Bharati and Singh [8] proposed completely intuitionistic fuzzy LP problems that are based on the sign distance between triangular intuitionistic fuzzy integers. Gani and Ponnalagu [15] proposed a method of solving a fuzzy LP problems based on the intuitionistic triangular fuzzy numbers. Sidhu and Kumar [25] employed a ranking algorithm to solve intuitionistic fuzzy LP problems. To defuzzify triangular intuitionistic fuzzy numbers, Nagoorgani and Ponnalagu [23] devised an accuracy function.

However, the intuitionistic fuzzy set does not accurately represent the human decision-making process. Because making the best decision is basically a matter of organising and explaining facts, Smarandache [27] in 1999 proposed the notion of neutrosophic set theory to deal with ambiguous, imprecise, and inconsistent data. Neutrosophic set theory replicates human decision-making by taking into account all parts of the process. The phrase "neutrosophic set" refers to popularisation of fuzzy and intuitionistic fuzzy sets, in which each element has a membership function for truth, indeterminacy, and falsehood. As a result, the neutrosophic set may swiftly and effectively ingest incorrect, unclear, and maladjusted information [11]. In uncertainty modelling, neutrosophic sets play a significant role. The advancement of uncertainty theory is essential in the formulation of real-life scientific mathematical models and its extensions have been applied in a wide variety of fields [28] including computer science [14], engineering [17], mathematics [9, 4], health care [5, 22] etc. In addition, they have been applied to much multi-criteria decision making problems [16, 24, 2]. A neutrosophic set's main advantage is that it enhances decision-making by accounting for degrees of truth, falsehood, and indeterminacy. The degree of indeterminacy is frequently seen as a free component with a significant commitment in decision-making. Because real-world situations are unpredictable, triangular neutrosophic linear programming is preferred to classical linear programming. The neutrosophic LP problems are more beneficial than crisp LP problems since the decision maker is not needed to establish a rigorous formulation in his or her formulation of the problem. It is recommended that neutrosophic LP concerns be employed to minimise unrealistic modelling. Abdel-Basset et al. [1] proposed a novel method for solving the fully neutrosophic linear programming problems based on Tripezoidal neutrosophic numbers which was modified by Singh et al. [26] to solve fully neutrosophic linear programming problems. Edalatpanah [13] proposed a direct model to solve triangular neutrosophic linear programming. Wang et al. [29] used a triangular neutrosophic numbers to solve multi objective linear programming problems. Khatter [18] proposed a model to convert each triangular neutrosophic number in a linear programming problem to a weighted value using a possibilistic mean to determine the crisp linear programming problem. Das and Chakraborty [10] employed a pentagonal neutrosophic number and developed a method for translating it to the corresponding crisp LP problem using a ranking function. Bera and Mahapatra [7] used a single valued trapezoidal neutrosophic number to linear programming problems in the simplex method. Abdelfattah [3] proposed a parametric approach to solve neutrosophic linear programming models. We may now define a neutrosophic LP problem as one in which at least one coefficient is represented by a neutrosophic number as a result of ambiguous, inconsistent, and uncertain data. We proposed a study to solve NLP challenges based on past research. Ranking functions have been introduced to transform neutrosophic LP difficulties into crisp problems, one for each problem type. The proposed model was used to address both maximisation and minimization problems as well as mixed constraint problems.

The remainder of this study is organised as follows:

In Section 2, introduces some basic arithmetic operations of the neutrosophic set. Section 3 presents the formularization of neutrosophic LP models, whereas Section 4 presents the recommended strategy for addressing neutrosophic LP problems. In Section 5, the suggested technique is used to solve numerical examples given by Abdelfattah [3]. Finally, in Section 6, the benefits of current methods are emphasised, and future directions are discussed.

2 Preliminary

Definition 2.1. [11] *Triangular neutrosophic number (TNN) is denoted by $\widehat{X} = \langle x^L, x^M, x^U; \phi_x, \varphi_x, \psi_x \rangle$, where the three membership functions for the truth, indeterminacy, and falsity of x can be defined as follows:*

$$\tau(x) = \begin{cases} \dfrac{x - x^L}{x^M - x^L}\phi_x, & x^L \leq x \leq x^M \\ \phi_x, & x = x^M \\ \dfrac{x^U - x}{x^U - x^M}\phi_x, & x^M \leq x \leq x^U \\ 0, & otherwise \end{cases} \tag{1}$$

$$\iota(x) = \begin{cases} \dfrac{x - x^L}{x^M - x^L}\varphi_x, & x^L \leq x \leq x^M \\ \varphi_x, & x = a^M \\ \dfrac{x^U - x}{x^U - x^M}\varphi_x & x^M \leq x \leq x^U \\ 1, & otherwise \end{cases} \tag{2}$$

$$\nu(x) = \begin{cases} \dfrac{x - x^L}{x^M - x^L}\psi_x, & x^L \leq x \leq x^M \\ \psi_x, & x = x^M \\ \dfrac{x^U - x}{x^U - x^M}\psi_x, & x^M \leq x \leq x^U \\ 1, & otherwise \end{cases} \tag{3}$$

where $0 \leq \tau(x) + \iota(x) + \nu(x) \leq 3,\ x \in \widehat{X}$.

Definition 2.2. [11] *Suppose $\widehat{X}_1 = \langle x_1^L, x_1^M, x_1^U; \phi_{x_1}, \varphi_{x_1}, \psi_{x_1} \rangle$ and $\widehat{X}_2 = \langle x_2^L, x_2^M, x_2^U; \phi_{x_2}, \varphi_{x_2}, \psi_{x_2} \rangle$ two TNNs. Then The arithmetic relationships are stated as follows:*

1. $\widehat{X}_1 \oplus \widehat{X}_2 = \langle x_1^L + x_2^L, x_1^M + x_2^M, x_1^U + x_2^U; \phi_{x_1} \wedge \phi_{x_2}, \varphi_{x_1} \vee \varphi_{x_2}, \psi_{x_1} \vee \psi_{x_2} \rangle$.

2. $\widehat{X}_1 - \widehat{X}_1 = \langle x_1^L - x_2^U, x_1^M - x_2^M, x_1^U - x_2^L; \phi_{x_1} \wedge \phi_{x_2}, \varphi_{x_1} \vee \varphi_{x_2}, \psi_{x_1} \vee \psi_{x_2} \rangle$.

3. $\widehat{X}_1 \otimes \widehat{X}_1 = \langle x_1^L x_2^L, x_1^M x_2^M, x_1^U x_2^U; \phi_{x_1} \wedge \phi_{x_2}, \varphi_{x_1} \vee \varphi_{x_2}, \psi_{x_1} \vee \psi_{x_2} \rangle$.

4. $\lambda\widehat{X}_1 = \begin{cases} \langle \lambda x_1^L, \lambda x_1^M, \lambda x_1^U; \phi_{x_1}, \varphi_{x_1}, \psi_{x_1}\rangle, & \lambda > 0 \\ \langle \lambda x_1^U, \lambda x_1^M, \lambda x_1^L; \phi_{x_1}, \varphi_{x_1}, \psi_{x_1}\rangle, & \lambda < 0 \end{cases}$

where $a \wedge b = \min(a, b)$ *and* $a \vee b = \max(a, b)$.

Definition 2.3. *Based on the definition (2.2), the ranking function can be defined as*

$$R(\widehat{X}) = \begin{cases} \dfrac{2(x^L + x^U) - x^M}{3} + \phi_x - \varphi_x - \psi_x, & \text{if } \widehat{X} \text{ be a TNN} \\ \widehat{X}, & \text{if } \widehat{X} \text{ is real number} \end{cases} \tag{4}$$

$$R(\lambda\widehat{X}) = \begin{cases} \lambda\Big(R(\widehat{X}) - (\phi_x - \varphi_x - \psi_x)\Big) + (\phi_x - \varphi_x - \psi_x), & \text{if } \lambda > 0 \\ \lambda\Big(R(\widehat{X}) - (\phi_x - \varphi_x - \psi_x)\Big) - (\phi_x - \varphi_x - \psi_x), & \text{if } \lambda < 0 \end{cases} \tag{5}$$

Definition 2.4. *Suppose* $\widehat{X_1}$ *and* $\widehat{X_2}$ *be two TNNs, then two triangular number can be compared by*

1. $\widehat{X_1} \le \widehat{X_2}$ iff $R(\widehat{X_1}) \le R(\widehat{X_2})$.
2. $\widehat{X_1} = \widehat{X_2}$ iff $R(\widehat{X_1}) = R(\widehat{X_2})$.

where $R(.)$ *is a ranking function.*

Example 2.5. Let us consider $\widehat{X_1} = \langle 10, 14, 17; 0.6, 0.2, 0.3\rangle$ and $\widehat{X_2} = \langle 10, 16, 18; 0.4, 0.5, 0.7\rangle$ are the TNN. Then

(a) $R(\widehat{X_1}) = \dfrac{2(10+17) - 14}{3} + (0.6 - 0.2 - 0.3) = 13.433.$

(b) $5\widehat{A} = \langle 50, 70, 85; 0.6, 0.2, 0.3\rangle$ then $R(5\widehat{X_1}) = \dfrac{2(50+85) - 70}{3} + (0.6 - 0.2 - 0.3) = 66.76$, by using equation (5) we have $R(5\widehat{X_1}) = 5\Big(13.433 - (0.6 - 0.2 - 0.3)\Big) + (0.6 - 0.2 - 0.3) = 66.76$

(c) $-5\widehat{X_1} = \langle -85, -70, -50; 0.6, 0.2, 0.3\rangle$ then $R(-5\widehat{X_1}) = \dfrac{2(-50-85) + 70}{3} - (0.6 - 0.2 - 0.3) = -66.76$, by using equation (5) we have $R(-5\widehat{X_1}) = -5\Big(13.433 - (0.6 - 0.2 - 0.3)\Big) - (0.6 - 0.2 - 0.3) = -66.76$

(d) Since $R(\widehat{X_1}) = 13.433$ and $R(\widehat{X_2}) = 12.533$, then $\widehat{X_1} > \widehat{X_2}$.

Theorem 2.6. *Let us consider* $\widehat{X}_1 = \langle x_1^L, x_1^M, x_1^U; \phi_{x_1}, \varphi_{x_1}, \psi_{x_1}\rangle$ *and* $\widehat{X}_2 = \langle x_2^L, x_2^M, x_2^U; \phi_{x_2}, \varphi_{x_2}, \psi_{x_2}\rangle$ *are the TNN. Then*

$$\begin{aligned} R(\widehat{X_1} - \widehat{X_2}) = R(\widehat{X_1}) - R(\widehat{X_2}) - \big[(\phi_{x_1} - \phi_{x_2}) - (\varphi_{x_1} - \varphi_{x_2}) - (\psi_{x_1} - \psi_{x_2})\big] + \phi_{x_1} \wedge \phi_{x_2} \\ - \varphi_{x_1} \vee \varphi_{x_2} - \psi_{x_1} \vee \psi_{x_2}. \end{aligned} \tag{6}$$

Proof. Since, $\widehat{X}_1 - \widehat{X}_1 = \langle x_1^L - x_2^L, x_1^M - x_2^M, x_1^U - x_2^U; \phi_{x_1} \wedge \phi_{x_2}, \varphi_{x_1} \vee \varphi_{x_2}, \psi_{x_1} \vee \psi_{x_2}\rangle$, then

$$\begin{aligned} R(\widehat{X_1} - \widehat{X_2}) &= \frac{2(x_1^L - x_2^L + x_1^U - x_2^U) - (x_1^M - x_2^M)}{3} + \phi_{x_1} \wedge \phi_{x_2} - \varphi_{x_1} \vee \varphi_{x_2} - \psi_{x_1} \vee \psi_{x_2} \\ &= \frac{2(x_1^L + x_1^U) - x_1^M}{3} - \frac{2(x_2^L + x_2^U) - x_2^M}{3} + \phi_{x_1} \wedge \phi_{x_2} - \varphi_{x_1} \vee \varphi_{x_2} - \psi_{x_1} \vee \psi_{x_2} \\ &= \big[R(\widehat{X_1}) - (\phi_{x_1} - \varphi_{x_1} - \psi_{x_1})\big] - \big[R(\widehat{X_2}) - (\phi_{x_2} - \varphi_{x_2} - \psi_{x_2})\big] \\ &\qquad + \phi_{x_1} \wedge \phi_{x_2} - \varphi_{x_1} \vee \varphi_{x_2} - \psi_{x_1} \vee \psi_{x_2} \\ &= R(\widehat{X_1}) - R(\widehat{X_2}) - \big[\phi_{x_1} - \phi_{x_2} - (\varphi_{x_1} - \varphi_{x_2}) - (\psi_{x_1} - \psi_{x_2})\big] \\ &\qquad + \phi_{x_1} \wedge \phi_{x_2} - \varphi_{x_1} \vee \varphi_{x_2} - \psi_{x_1} \vee \psi_{x_2} \end{aligned}$$

□

Theorem 2.7. *Let $\widehat{X_i} = \langle x_i^L, x_i^M, x_i^U; \phi_{x_i}, \varphi_{x_i}, \psi_{x_i}\rangle$ be n TNNs. Then*

$$R\Big(\sum_{i=1}^{n}\widehat{X_i}\Big) = \sum_{i=1}^{n} R(\widehat{X_i}) - \sum_{i=1}^{n}(\phi_{x_i} - \varphi_{x_i} - \psi_{x_i}) + \bigwedge_{i=1}^{n}\phi_{x_i} - \bigvee_{i=1}^{n}\varphi_{x_i} - \bigvee_{i=1}^{n}\psi_{x_i} \tag{7}$$

Proof. Let $\widehat{X_i} = \langle x_i^L, x_i^M, x_i^U; \phi_{x_i}, \varphi_{x_i}, \psi_{x_i}\rangle$, then

$$\sum_{i=1}^{n}\widehat{X_i} = \Big\langle \sum_{i=1}^{n} x_i^L, \sum_{i=1}^{n} x_i^M, \sum_{i=1}^{n} x_i^U; \bigwedge_{i=1}^{n}\phi_{x_i}, \bigvee_{i=1}^{n}\varphi_{x_i}, \bigvee_{i=1}^{n}\psi_{X_i}\Big\rangle$$

$$\begin{aligned}
R\Big(\sum_{i=1}^{n}\widehat{A_i}\Big) &= \frac{2\big(\sum_{i=1}^{n} x_i^L + \sum_{i=1}^{n} x_i^U\big) - \sum_{i=1}^{n} x_i^M}{3} + \bigwedge_{i=1}^{n}\phi_{x_i} - \bigvee_{i=1}^{n}\varphi_{x_i} - \bigvee_{i=1}^{n}\psi_{x_i} \\
&= \sum_{i=1}^{n}\Big(\frac{2(x_i^L + x_i^U) - x_i^M}{3}\Big) + \bigwedge_{i=1}^{n}\phi_{x_i} - \bigvee_{i=1}^{n}\varphi_{x_i} - \bigvee_{i=1}^{n}\psi_{x_i} \\
&= \sum_{i=1}^{n}\Big(\frac{2(x_i^L + x_i^U) - x_i^M}{3} + (\phi_{x_i} - \varphi_{x_i} - \psi_{x_i})\Big) - \sum_{i=1}^{n}(\phi_{x_i} - \varphi_{x_i} - \psi_{x_i}) \\
&\quad + \bigwedge_{i=1}^{n}\phi_{x_i} - \bigvee_{i=1}^{n}\varphi_{x_i} - \bigvee_{i=1}^{n}\psi_{x_i} \\
&= \sum_{i=1}^{n}\Big(R(\widehat{X_i})\Big) - \sum_{i=1}^{n}(\phi_{x_i} - \varphi_{x_i} - \psi_{x_i}) + \bigwedge_{i=1}^{n}\phi_{x_i} - \bigvee_{i=1}^{n}\varphi_{x_i} - \bigvee_{i=1}^{n}\psi_{x_i}.
\end{aligned}$$

□

Theorem 2.8. *Let $\widehat{X_i} = \langle x_i^L, x_i^M, x_i^U; \phi_{x_i}, \varphi_{x_i}, \psi_{x_i}\rangle$ be n TNNs and if $\lambda_i > 0$. Then*

$$R\Big(\sum_{i=1}^{n}\lambda_i\widehat{X_i}\Big) = \sum_{i=1}^{n}\lambda_i\Big(R(\widehat{X_i}) - (\phi_{x_i} - \varphi_{x_i} - \psi_{A_i})\Big) + \bigwedge_{i=1}^{n}\phi_{x_i} - \bigvee_{i=1}^{n}\varphi_{x_i} - \bigvee_{i=1}^{n}\psi_{x_i} \tag{8}$$

Proof.

For $\lambda_i > 0$, $\sum_{i=1}^{n}\lambda_i\widehat{X_i} = \Big\langle \sum_{i=1}^{n}\lambda_i x_i^L, \sum_{i=1}^{n}\lambda_i x_i^M, \sum_{i=1}^{n}\lambda_i x_i^U; \bigwedge_{i=1}^{n}\phi_{x_i}, \bigvee_{i=1}^{n}\varphi_{x_i}, \bigvee_{i=1}^{n}\psi_{x_i}\Big\rangle$, then

From definition 2.2, we have

$$\begin{aligned}
R\Big(\sum_{i=1}^{n}\lambda_i\widehat{X_i}\Big) &= \frac{2\big(\sum_{i=1}^{n}\lambda_i x_i^L + \sum_{i=1}^{n}\lambda_i x_i^U\big) - \sum_{i=1}^{n}\lambda_i x_i^M}{3} + \bigwedge_{i=1}^{n}\phi_{x_i} - \bigvee_{i=1}^{n}\varphi_{x_i} - \bigvee_{i=1}^{n}\psi_{x_i} \\
&= \sum_{i=1}^{n}\lambda_i\Big(\frac{2(x_i^L + x_i^U) - x_i^M}{3}\Big) + \bigwedge_{i=1}^{n}\phi_{x_i} - \bigvee_{i=1}^{n}\varphi_{x_i} - \bigvee_{i=1}^{n}\psi_{x_i} \\
&= \sum_{i=1}^{n}\lambda_i\Big(\frac{2(x_i^L + x_i^U) - x_i^M}{3} + (\phi_{x_i} - \varphi_{x_i} - \psi_{x_i})\Big) - \sum_{i=1}^{n}\lambda_i(\phi_{x_i} - \varphi_{x_i} - \psi_{x_i}) \\
&\quad + \bigwedge_{i=1}^{n}\phi_{x_i} - \bigvee_{i=1}^{n}\varphi_{x_i} - \bigvee_{i=1}^{n}\psi_{x_i} \\
&= \sum_{i=1}^{n}\lambda_i\Big(R(\widehat{X_i}) - (\phi_{x_i} - \varphi_{x_i} - \psi_{x_i})\Big) + \bigwedge_{i=1}^{n}\phi_{x_i} - \bigvee_{i=1}^{n}\varphi_{x_i} - \bigvee_{i=1}^{n}\psi_{x_i}
\end{aligned}$$

□

Theorem 2.9. *Let* $\widehat{A_i} = \langle x_i^L, x_i^M, x_i^U; \phi_{x_i}, \varphi_{x_i}, \psi_{x_i}\rangle$ *be* n *TNNs and if* $\lambda_i < 0$. *Then*

$$R\Big(\sum_{i=1}^{n}\lambda_i\widehat{X_i}\Big) = \sum_{i=1}^{n}\lambda_i\Big(R(\widehat{X_i}) - (\phi_{x_i} - \varphi_{x_i} - \psi_{x_i})\Big) - 2\sum_{i=1}^{n}(\phi_{x_i} - \varphi_{x_i} - \psi_{x_i}) + \bigwedge_{i=1}^{n}\phi_{x_i} - \bigvee_{i=1}^{n}\varphi_{x_i} - \bigvee_{i=1}^{n}\psi_{x_i} \tag{9}$$

Proof. For $\lambda_i < 0$, using theorem 2.7 and defination 2.2, we have

$$\begin{aligned} R\Big(\sum_{i=1}^{n}\lambda_i\widehat{X_i}\Big) &= \sum_{i=1}^{n}\Big(R(\lambda_i\widehat{X_i})\Big) - \sum_{i=1}^{n}(\phi_{x_i} - \varphi_{x_i} - \psi_{x_i}) + \bigwedge_{i=1}^{n}\phi_{x_i} - \bigvee_{i=1}^{n}\varphi_{x_i} - \bigvee_{i=1}^{n}\psi_{x_i} \\ &= \sum_{i=1}^{n}\Big(\lambda_i\big(R(\widehat{X_i}) - (\phi_{x_i} - \varphi_{x_i} - \psi_{x_i})\big) - (\phi_{x_i} - \varphi_{x_i} - \psi_{x_i})\Big) - \sum_{i=1}^{n}(\phi_{x_i} - \varphi_{x_i} - \psi_{x_i}) \\ &\quad + \bigwedge_{i=1}^{n}\phi_{x_i} - \bigvee_{i=1}^{n}\varphi_{x_i} - \bigvee_{i=1}^{n}\psi_{x_i} \\ &= \sum_{i=1}^{n}\lambda_i\Big(R(\widehat{X_i}) - (\phi_{x_i} - \varphi_{x_i} - \psi_{x_i})\Big) - 2\sum_{i=1}^{n}(\phi_{x_i} - \varphi_{x_i} - \psi_{x_i}) + \bigwedge_{i=1}^{n}\phi_{x_i} - \bigvee_{i=1}^{n}\varphi_{x_i} - \bigvee_{i=1}^{n}\psi_{x_i} \end{aligned}$$

□

Theorem 2.10. *Let* $\widehat{X}_i = \langle x_i^L, x_i^M, x_i^U; \phi_{x_i}, \varphi_{x_i}, \psi_{x_i}\rangle$ *and* $\widehat{Y}_j = \langle y_j^L, y_j^M, y_j^U; \phi_{y_j}, \varphi_{y_j}, \psi_{y_j}\rangle$ *are the TNNs, and* $\lambda_i, \delta_j > 0$ *for* $i = 1, 2, 3, \cdots, n \quad j = 1, 2, 3, \cdots, m,$. *Then*

$$\begin{aligned} R\Big(\sum_{i=1}^{n}\lambda_i\widehat{X_i} - \sum_{j=1}^{m}\delta_j\widehat{Y}_j\Big) &= \sum_{i=1}^{n}\lambda_i\Big(R(\widehat{X_i}) - (\phi_{x_i} - \varphi_{x_i} - \psi_{x_i})\Big) - \sum_{j=1}^{m}\delta_j\Big(R(\widehat{Y}_j) - (\phi_{y_j} - \varphi_{y_j} - \psi_{y_j})\Big) \\ &\quad + \Big(\bigwedge_{i=1}^{n}\phi_{x_i} \wedge \bigwedge_{j=1}^{m}\phi_{y_j}\Big) - \Big(\bigvee_{i=1}^{n}\varphi_{x_i} \vee \bigvee_{j=1}^{m}\varphi_{y_j}\Big) - \Big(\bigvee_{i=1}^{n}\psi_{x_i} \vee \bigvee_{j=1}^{m}\psi_{y_j}\Big) \end{aligned} \tag{10}$$

Proof.

$$\begin{aligned}
R\Big(\sum_{i=1}^{n}\lambda_i\widehat{X_i}-\sum_{j=1}^{m}\delta_j\widehat{Y_j}\Big) &= R\big(\sum_{i=1}^{n}\lambda_i\widehat{X_i}\big)-R\big(\sum_{j=1}^{m}\delta_j\widehat{Y_j}\big)-\Big[\bigwedge_{i=1}^{n}\phi_{x_i}-\bigwedge_{j=1}^{m}\phi_{y_j}-\Big(\bigvee_{i=1}^{n}\varphi_{x_i}-\bigvee_{j=1}^{m}\varphi_{y_j}\Big)\\
&\quad-\Big(\bigvee_{i=1}^{n}\psi_{x_i}-\bigvee_{j=1}^{m}\psi_{y_j}\Big)\Big]+\Big(\bigwedge_{i=1}^{n}\phi_{x_i}\wedge\bigwedge_{j=1}^{m}\phi_{y_j}\Big)-\Big(\bigvee_{i=1}^{n}\varphi_{x_i}\vee\bigvee_{j=1}^{m}\varphi_{y_j}\Big)-\Big(\bigvee_{i=1}^{n}\psi_{x_i}\vee\bigvee_{j=1}^{m}\psi_{y_j}\Big)\\
&=\sum_{i=1}^{n}\lambda_i\Big(R(\widehat{X_i})-(\phi_{x_i}-\varphi_{x_i}-\psi_{x_i})\Big)+\bigwedge_{i=1}^{n}\phi_{x_i}-\bigvee_{i=1}^{n}\varphi_{x_i}-\bigvee_{i=1}^{n}\psi_{x_i}-\Big[\sum_{j=1}^{m}\delta_j\Big(R(\widehat{Y_j})-\bigvee_{j=1}^{m}\varphi_{y_j}\Big)\\
&\quad-(\phi_{y_j}-\varphi_{y_j}-\psi_{y_j})\Big)+\bigwedge_{j=1}^{m}\phi_{y_j}-\bigvee_{i=1}^{m}\varphi_{y_j}-\bigvee_{i=1}^{m}\psi_{y_j}\Big]-\Big[\bigwedge_{i=1}^{n}\phi_{x_i}-\bigwedge_{j=1}^{m}\phi_{y_j}-\Big(\bigvee_{i=1}^{n}\varphi_{x_i}\\
&\quad-\Big(\bigvee_{i=1}^{n}\psi_{x_i}-\bigvee_{j=1}^{m}\psi_{y_j}\Big)\Big]+\Big(\bigwedge_{i=1}^{n}\phi_{x_i}\wedge\bigwedge_{j=1}^{m}\phi_{y_j}\Big)-\Big(\bigvee_{i=1}^{n}\varphi_{x_i}\vee\bigvee_{j=1}^{m}\varphi_{y_j}\Big)-\Big(\bigvee_{i=1}^{n}\psi_{x_i}\vee\bigvee_{j=1}^{m}\psi_{y_j}\Big)\\
&=\sum_{i=1}^{n}\lambda_i\Big(R(\widehat{X_i})-(\phi_{x_i}-\varphi_{x_i}-\psi_{x_i})\Big)-\sum_{j=1}^{m}\delta_j\Big(R(\widehat{Y_j})-(\phi_{y_j}-\varphi_{y_j}-\psi_{y_j})\Big)+\Big(\bigwedge_{i=1}^{n}\phi_{x_i}\wedge\bigwedge_{j=1}^{m}\phi_{y_j}\Big)\\
&\quad-\Big(\bigvee_{i=1}^{n}\varphi_{x_i}\vee\bigvee_{j=1}^{m}\varphi_{y_j}\Big)-\Big(\bigvee_{i=1}^{n}\psi_{x_i}\vee\bigvee_{j=1}^{m}\psi_{y_j}\Big)
\end{aligned}$$

□

3 Triangular Neutrosophic Linear Programming Problem

Consider the standard form of linear programming problem with m constraints and n variables.

$$\begin{aligned}
\text{Min / Max}\ &\sum_{j=1}^{n}c_jx_j\\
\text{s.t.}\ &\sum_{j=1}^{n}\alpha_{ij}x_j\ (\leq,=,\geq)\ b_j,\quad\forall\ i=1,2,3,\cdots,m.
\end{aligned}\tag{11}$$

The corresponding neutrosophic linear programming problem having all coefficients and resources are represented triangular neutrosophic numbers as follows:

$$\begin{aligned}
\text{Min / Max}\ &\sum_{j=1}^{n}\widehat{c_j}x_j\\
\text{s.t.}\ &\sum_{j=1}^{n}\widehat{\alpha_{ij}}x_j\ (\leq,=,\geq)\ \widehat{b_i}\quad\forall i=1,2,3,\cdots,m.
\end{aligned}\tag{12}$$

where $\widehat{c_j}=\langle c_j^L,c_j^M,c_j^U;\phi_{c_j},\varphi_{c_j},\psi_{c_j}\rangle,\widehat{\alpha_{ij}}=\langle\alpha_{ij}^L,\alpha_{ij}^M,\alpha_{ij}^U;\phi_{\alpha_{ij}},\varphi_{\alpha_{ij}},\psi_{\alpha_{ij}}\rangle$ and $\widehat{b_i}=\langle b_i^L,b_i^M,b_i^U;\phi_{b_i},\varphi_{b_i},\psi_{b_i}\rangle$, that is

$$\begin{aligned} \text{Min / Max } & \sum_{j=1}^{n} \langle c_j^L, c_j^M, c_j^U; \phi_{c_j}, \varphi_{c_j}, \psi_{c_j} \rangle x_j \\ \text{s.t. } & \sum_{j=1}^{n} \langle \alpha_{ij}^L, \alpha_{ij}^M, \alpha_{ij}^U; \phi_{\alpha_{ij}}, \varphi_{\alpha_{ij}}, \psi_{\alpha_{ij}} \rangle x_j \ (\leq, =, \geq) \ \langle b_i^L, b_i^M, b_i^U; \phi_{b_i}, \varphi_{b_i}, \psi_{b_i} \rangle \\ & \quad \forall \ i = 1, 2, 3, \cdots, m. \end{aligned}$$

which is the general form of fully Triangular neutrosophic linear programming problem.

4 Method for Solving Triangular Neutrosophic Linear Programming Problem

Consider two scenarios for a completely triangular neutrosophic LP problem with n variables and m constraints in a standard form.

Step 1: Check, if the triangular neutrosophic linear programming problem is one of the scenarios provided.

Scenario 1: Suppose the triangular neutrosophic LP problem does not contain any negative term in the objective function and constraint.

$$\begin{aligned} \text{Min / Max } & \sum_{j=1}^{n} \widehat{c_j} x_j \\ \text{s.t. } & \sum_{j=1}^{k} \widehat{\alpha_{ij}} x_j \ (\leq, =, \geq) \ \widehat{b_i}, \quad \forall \ i = 1, 2, 3, \cdots, m. \end{aligned} \tag{13}$$

Scenario 2: Suppose the TNLP problem contain any negative term in the objective function and constraint.

$$\begin{aligned} \text{Min / Max } & \sum_{j=1}^{s} \widehat{c_j} x_j - \sum_{j=s+1}^{n} \widehat{c_j} x_j \\ \text{s.t. } & \sum_{j=1}^{k} \widehat{\alpha_{ij}} x_j - \sum_{j=k+1}^{n} \widehat{\alpha_{ij}} x_j \ (\leq, =, \geq) \ \widehat{b_i}, \quad \forall \ i = 1, 2, 3, \cdots, m. \end{aligned}$$

where

$$\begin{aligned} \widehat{c_j} &= \langle c_j^L, c_j^M, c_j^U; \phi_{c_j}, \varphi_{c_j}, \psi_{c_j} \rangle, \\ \widehat{\alpha_{ij}} &= \langle \alpha_{ij}^L, \alpha_{ij}^M, \alpha_{ij}^U; \phi_{\alpha_{ij}}, \varphi_{\alpha_{ij}}, \psi_{\alpha_{ij}} \rangle, \\ \widehat{b_i} &= \langle b_i^L, b_i^M, b_i^U; \phi_{b_i}, \varphi_{b_i}, \psi_{b_i} \rangle. \end{aligned}$$

Step 2: Applying the ranking function in the TNLP problem based on definition (2.2) and (2.3), and theorem (2.6)-(2.10) and convert it into crips LP problem.

Scenario 1:

$$\begin{aligned} \text{Min / Max } & R\Big(\sum_{j=1}^{n} \widehat{c_j} x_j \Big) \\ \text{s.t. } & R\Big(\sum_{j=1}^{n} \widehat{\alpha_{ij}} x_j \Big) \ (\leq, =, \geq) \ R\Big(\widehat{b_i}\Big), \quad \forall \ i = 1, 2, 3, \cdots, m. \end{aligned}$$

that is

$$\begin{aligned}
\text{Min / Max } &\sum_{j=1}^{n}\Big(R(\widehat{c_j})-(\phi_{c_j}-\varphi_{c_j}-\psi_{c_j})\Big)x_j+\bigwedge_{j=1}^{n}\phi_{c_j}-\bigvee_{j=1}^{n}\varphi_{c_j}-\bigvee_{j=1}^{n}\psi_{c_j}\\
\text{s.t. } &\sum_{j=1}^{k}\Big(R(\widehat{\alpha_{ij}})-(\phi_{\alpha_{ij}}-\varphi_{\alpha_{ij}}-\psi_{\alpha_{ij}})\Big)x_j+\bigwedge_{j=1}^{n}\phi_{\alpha_{ij}}-\bigvee_{j=1}^{n}\varphi_{\alpha_{ij}}-\bigvee_{j=1}^{n}\psi_{\alpha_{ij}}\ (\leq,=,\geq)\ R\Big(\widehat{b_i}\Big)\\
&\quad \forall\ i=1,2,3,\cdots,m.
\end{aligned}$$

Scenario 2:

$$\begin{aligned}
\text{Min / Max } &R\Big(\sum_{j=1}^{s}\widehat{c_j}x_j-\sum_{j=s+1}^{n}\widehat{c_j}x_j\Big)\\
\text{s.t } &R\Big(\sum_{j=1}^{k}\widehat{\alpha_{ij}}x_j-\sum_{j=k+1}^{n}\widehat{\alpha_{ij}}x_j\Big)(\leq,=,\geq)\ R\Big(\widehat{b_i}\Big),\quad \forall\ i=1,2,3,\cdots,m.
\end{aligned}$$

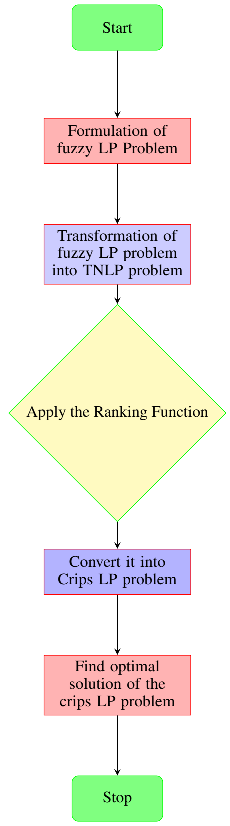
that is

$$\begin{aligned}
\text{Min / Max } &\sum_{j=1}^{s}\Big(R(\widehat{c_j})-(\phi_{c_j}-\varphi_{c_j}-\psi_{c_j})\Big)x_j-\sum_{j=s+1}^{n}\Big(R(\widehat{c_j})-(\phi_{c_j}-\varphi_{c_j}-\psi_{c_j})\Big)x_j\\
&+\bigwedge_{j=1}^{n}\phi_{c_j}-\bigvee_{j=1}^{n}\varphi_{c_j}-\bigvee_{j=1}^{n}\psi_{c_j}\\
\text{s.t. } &\sum_{j=1}^{k}\Big(R(\widehat{\alpha_{ij}})-(\phi_{\alpha_{ij}}-\varphi_{\alpha_{ij}}-\psi_{\alpha_{ij}})\Big)x_j-\sum_{j=k+1}^{n}\Big(R(\widehat{\alpha_{ij}})x_j-(\phi_{\alpha_{ij}}-\varphi_{\alpha_{ij}}-\psi_{\alpha_{ij}})\Big)\\
&+\bigwedge_{j=1}^{n}\phi_{\alpha_{ij}}-\bigvee_{j=1}^{n}\varphi_{\alpha_{ij}}-\bigvee_{j=1}^{n}\psi_{\alpha_{ij}}(\leq,=,\geq)\ R\Big(\widehat{b_i}\Big),\quad \forall\ i=1,2,3,\cdots,m.
\end{aligned}$$

which are the crips LP problem.

Step 3: Solve this crips LP problem using any method and find the optimal solution.

The step by step solution procedure of triangular neutrosophic LP problems is shown in the given flow chart



5 Numerical Example

In this section, to prove the applicability and advantages of our proposed model of neutrosophic LP problems, we solved the same problem which introduced by Abdelfattah [3].

Example 5.1. (Minimization Problem)
Let us consider a minimization problem

$$\begin{aligned} \text{Min} \quad & \langle 2,6,8;1,0,0\rangle x_1 + \langle 1,3,6;1,0,0\rangle x_2 \\ \text{s.t.} \quad & \langle 0.5,2,3;0.7,0.4,0.1\rangle x_1 + \langle 0,4,6;0.6,0.3,0.1\rangle x_2 \geq \langle 12,16,19;0.5,0.3,0.5\rangle, \\ & \langle 1,4,12;0.5,0.4,0.2\rangle x_1 + \langle 1,3,10;0.7,0.4,0.3\rangle x_2 \geq \langle 20,24,28;0.8,0.3,0.3\rangle \\ \text{and } & x_1, x_2 \geq 0. \end{aligned}$$

We have used the ranking function in the above neutrosophic linear programming problem, it follows that

$$\begin{aligned} \text{Min} \quad & R\Big(\langle 2,6,8;1,0,0\rangle x_1 + \langle 1,3,6;1,0,0\rangle x_2\Big) \\ \text{s.t.} \quad & R\Big(\langle 0.5,2,3;0.7,0.4,0.1\rangle x_1 + \langle 0,4,6;0.6,0.3,0.1\rangle x_2\Big) \geq R\Big(\langle 12,16,19;0.5,0.3,0.5\rangle\Big) \\ & R\Big(\langle 1,4,12;0.5,0.4,0.2\rangle x_1 + \langle 1,3,10;0.7,0.4,0.3\rangle x_2\Big) \geq R\Big(\langle 20,24,28;0.8,0.3,0.3\rangle\Big) \\ \text{and } & x_1, x_2 \geq 0. \end{aligned}$$

By using definition (2.2) and theorem (2.8), we have

$$\begin{aligned} \text{Min} \quad & 4.67x_1 + 3.67x_2 + 1 \\ \text{s.t.} \quad & 1.67x_1 + 2.67x_2 + 0.2 \geq 15.03 \\ & 7.33x_1 + 6.33x_2 - 0.2 \geq 24.2 \\ \text{and } & x_1, x_2 \geq 0. \end{aligned}$$

The optimal solution of the problem as $x_1 = 0.0000,\ x_2 = 5.5543$ and $Z^* = 21.3843$.

Example 5.2. (Maximization Problem)
Let us consider the maximization problem

$$\begin{aligned} \text{Max } & \langle 30, 40, 50; 0.7, 0.4, 0.3\rangle x_1 + \langle 40, 50, 60; 0.6, 0.5, 0.2\rangle x_2 \\ \text{s.t. } & \langle 0.5, 1, 3; 0.6, 0.4, 0.1\rangle x_1 + \langle 0, 2, 6; 0.6, 0.4, 0.1\rangle x_2 \leq \langle 20, 40, 60; 0.4, 0.3, 0.5\rangle \\ & \langle 1, 4, 12; 0.4, 0.3, 0.2\rangle x_1 + \langle 1, 3, 10; 0.7, 0.4, 0.3\rangle x_2 \leq \langle 100, 120, 140; 0.7, 0.4, 0.3\rangle \\ \text{and } & x_1, x_2 \geq 0. \end{aligned}$$

We have used the ranking function in the above neutrosophic linear programming problem, it follows that

$$\begin{aligned} \text{Max } & R\Big(\langle 30, 40, 50; 0.7, 0.4, 0.3\rangle x_1 + \langle 40, 50, 60; 0.6, 0.5, 0.2\rangle x_2\Big) \\ \text{s.t. } & R\Big(\langle 0.5, 1, 3; 0.6, 0.4, 0.1\rangle x_1 + \langle 0, 2, 6; 0.6, 0.4, 0.1\rangle x_2\Big) \leq R\Big(\langle 20, 40, 60; 0.4, 0.3, 0.5\rangle\Big) \\ & R\Big(\langle 1, 4, 12; 0.4, 0.3, 0.2\rangle x_1 + \langle 1, 3, 10; 0.7, 0.4, 0.3\rangle x_2\Big) \leq R\Big(\langle 100, 120, 140; 0.7, 0.4, 0.3\rangle\Big) \\ \text{and } & x_1, x_2 \geq 0. \end{aligned}$$

By using definition (2.2) and theorem (2.8), we have

$$\begin{aligned} \text{Max} \quad & 40x_1 + 50x_2 - 0.2 \\ \text{s.t.} \quad & 2x_1 + 3.33x_2 + 0.1 \leq 39.6 \\ & 7.3x_1 + 6.33x_2 - 0.3 \leq 126.3 \\ \text{and } & x_1, x_2 \geq 0. \end{aligned}$$

The optimal solution of the mixed constrained problem as $x_1 = 14.6008,\ x_2 = 3.0926$ and $Z^* = 738.1623$.

Example 5.3. (Mixed Constraint Problem)

$$\begin{aligned} \text{Max} \quad & \langle 380, 400, 430; 0.7, 0.4, 0.3\rangle x_1 + \langle 170, 200, 210; 0.6, 0.5, 0.2\rangle x_2 \\ \text{s.t.} \quad & \langle 0.5, 1, 3; 0.6, 0.5, 0.1\rangle x_1 + \langle 1, 2, 4; 0.6, 0.4, 0.2\rangle x_2 = \langle 50, 70, 100; 1, 0, 0\rangle \\ & \langle 1, 2, 5; 0.5, 0.3, 0.2\rangle x_1 + \langle 5, 8, 12; 0.7, 0.6, 0.5\rangle x_2 \geq \langle 72, 80, 89; 1, 0, 0\rangle \\ & \langle 0, 1, 4; 0.7, 0.5, 0.2\rangle x_1 + \langle 0, 0, 3; 0.8, 0.3, 0.2\rangle x_2 \leq \langle 30, 40, 55; 1, 0, 0\rangle \\ \text{and } & x_1, x_2 \geq 0. \end{aligned}$$

We have used the ranking function in the above neutrosophic linear programming problem, it follows that

$$\begin{aligned}
\text{Max} \quad & R\Big(\langle 380, 400, 430; 0.7, 0.4, 0.3\rangle x_1 + \langle 170, 200, 210; 0.6, 0.5, 0.2\rangle x_2\Big) \\
\text{s.t.} \quad & R\Big(\langle 0.5, 1, 3; 0.6, 0.5, 0.1\rangle x_1 + \langle 1, 2, 4; 0.6, 0.4, 0.2\rangle x_2\Big) = R\Big(\langle 50, 70, 100; 1, 0, 0\rangle\Big) \\
& R\Big(\langle 1, 2, 5; 0.5, 0.3, 0.2\rangle x_1 + \langle 5, 8, 12; 0.7, 0.6, 0.5\rangle x_2\Big) \geq R\Big(\langle 72, 80, 89; 1, 0, 0\rangle\Big) \\
& R\Big(\langle 0, 1, 4; 0.7, 0.5, 0.2\rangle x_1 + \langle 0, 0, 3; 0.8, 0.3, 0.2\rangle x_2\Big) \leq R\Big(\langle 30, 40, 55; 1, 0, 0\rangle\Big) \\
\text{and} \quad & x_1, x_2 \geq 0.
\end{aligned}$$

By using definition (2.2) and theorem (2.8), we have

$$\begin{aligned}
\text{Max} \quad & 406.67x_1 + 186.67x_2 - 0.2 \\
\text{s.t.} \quad & 2x_1 + 2.67x_2 - 0.1 = 77.67 \\
& 3.33x_1 + 8.6x_2 - 0.6 \geq 81.67 \\
& 2.33x_1 + 2x_2 \leq 44.33
\end{aligned}$$

The optimal solution of the mixed constrained problem as $x_1^* = 0.0000, x_2^* = 39.4257$ and $Z^* = 7359.4$.

6 Conclusion

Neutrosophic sets are a relatively new academic topic that is rapidly growing in popularity and being used for a wide range of decision-making concerns, particularly mathematical programming problems. The focus of this study is on linear programming models with neutrosophic coefficients. We solved the triangular neutrosophic linear programming problem in this article. We provided a unique ranking function for converting TNNs to their crisp counterparts, and we thoroughly investigated the arithmetic operations of triangular neutrosophic numbers. After utilising this ranking technique to convert the problem to its crisp values and solve it in any traditional way. Real-world modelling of triangular neutrosophic LP optimization may be simplified using the proposed approach, and it may be straightforward to use from a computational viewpoint. We used triangular neutrosophic linear programming problems to explain three basic problems offered by Abdelfattah [3]. We found that our proposed model is simpler, more efficient, and yields better outcomes than others.

Furthermore, researchers can successfully apply the concept of triangular neutrosophic number based linear programming strategy in a broad range of research domains. The real benefit of the proposed technique is that it can handle both symmetric and non-symmetric TNNs. Comparing results allows decision-makers to choose their own acceptance, imprecise, and falsehood criteria.

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