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An Optimized Method for Solving Membership-based Neutrosophic Linear Programming Problems

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Abstract: Linear Programming (LP) is an essential approach in mathematical programming because it is a viable technique used for addressing linear systems involving linear parameters and continuous constraints. The most important use of LP resides in solving the issues requiring resource management. Because many real-world issues are too complicated to be accurately characterized, indeterminacy is often present in every engineering planning process. Neutrosophic logic, which is an application of intuitionistic fuzzy sets, is a useful logic for dealing with indeterminacy. Neutrosophic Linear Programming (NLP) issues are essential in neutrosophic modelling because they may express uncertainty in the physical universe. Numerous techniques have been proposed to alleviate NLP difficulties. On the surface, the current approaches in the specialized literature are unable to tackle issues with non-deterministic variables. In other words, no method for solving a truly neutrosophic problem has been offered. For the first time, a unique approach is provided for tackling Fully Neutrosophic Linear Programming (FNLP) problems in this study. The proposed study uses a decomposition method to break the FNLP problem into three separate bounded problems. Then, these problems are solved using simplex techniques. Unlike other existing methods, the proposed method can solve NLP problems with neutrosophic values for variables. In this research, the decision-makers have the freedom to consider the variables with neutrosophic structure, while obtaining the optimal objective value as a crisp number. It should also be noted that the typical NLP problems, which can be solved by means of the existing methods, can also be solved through the method proposed in this paper.

Keywords: Linear programming, Neutrosophic sets, Neutrosophic linear programming, Direct method.

1. Introduction

Due to the complexity of fundamental problems in daily life, it is impossible to use definitive data to express these problems. In this regard, the Fuzzy Set (FS) (Zadeh, 1965) and its deployments such as interval-valued fuzzy sets (Zadeh, 1975), intuitionistic fuzzy sets (Atanassov, 1986), interval-valued intuitionistic fuzzy sets (Atanassov, 1991), type n-fuzzy sets (Dubois & Prade, 1980), neutrosophic sets (Smarandache, 1999), and plithogenic sets (Smarandache, 2018) have been proposed to deal with vague determined values (see Figure 1) (Nafei et al., 2021). However, most of the existing sets continue to be incapable of handling indeterminacy on their own. In order to address this limitation, Smarandache (1999) introduced Neutrosophic Sets (NSs). The NS is distinguished by three membership functions: Truth $T_N(x)$, Indeterminacy $I_N(x)$, and Falsity $F_N(x)$. With a new perspective, Wang et al. (2010) introduced the theory of Single-Valued Neutrosophic Sets (SVNSs), which has tremendous application in science and engineering.

Optimization is the way of life, and Linear programming (LP) is the simplest way to perform optimization. Mathematicians use LP as an appropriate viable strategy for resolving optimizing issues involving linear optimization techniques and linear conditions.

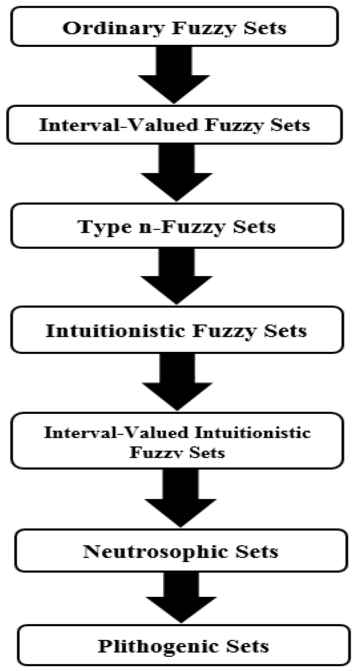

Figure 1. The extensions of FSs

The most important use of LP resides in solving capacity management systems. For example, linear optimization can always be used in transportation, in minimizing the costs of workshops and business

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operations, in deciding how to sell products, in optimizing resources, and so on. In recent decades, various linear programming methods have been proposed to solve optimization problems based on different sets. Das & Mandal (2017) presented a strategy for solving fuzzy fractional linear programming problems with the variables represented based on fuzzy sets. Using an improved score function, Garg (2018) presented a modified LP method for dealing with Multi-Criteria Decision-Making (MCDM) problems with partially-known weight information. Wang & Chen (2017) presented a modified approach for solving Multi-Attribute Decision-Making (MADM) problems to overcome the drawbacks of the existing methods. Bharati & Singh (2019) presented a novel algorithm for solving intuitionistic multi-objective linear programming problems. To solve the balanced and unbalanced intuitionistic fuzzy transportation problems, Kumar (2018) proposed two approaches based on linear programming techniques. Based on trapezoidal neutrosophic numbers and other ranking functions for converting NLP problems to crisp problems, Abdelbasset et al. (2019) proposed an innovative approach to deal with NLP problems. Das & Chakraborty (2021) presented a new strategy based on a new ranking function for converting neutrosophic values to crisp numbers. Nafei, Yuan & Nasseri (2019) proposed a new technique for solving Interval Neutrosophic Linear Programming (INLP) by developing a unique proprietary algorithm for transforming INLP problems into crisp problems. Zavadskas et al. (2020) proposed a novel MCDM methodology MULTIMOORA-mGqNN and then analyzed the effectiveness of different cable root management decisions for the application in the chemical industry. Maiti et al. (2020) proposed a neutrosophic goal programming strategy for a multi-level multi-objective linear programming problem. Hassanien et al. (2018) proposed a Neutrosophic C-Means approach for clustering.

Ranking neutrosophic values is an essential part of optimization (Smarandache & Guo, 2022). In this respect, Sing, Kumar & Appadoo (2019), and also Abdelbaset et al. (2019) proposed innovative methods using different ranking functions to deal with NLP problems. Although the existing methods can solve neutrosophic problems, they are unable to solve problems with neutrosophic variables. By all accounts, there is no technique for thoroughly addressing NLP issues (problems with non-deterministic variables) where neutrosophic values reflect all the parameters from the specialized literature. This study provides a novel strategy for breaking down the NLP issues into three crisp problems. Then, it solves them by using the current standard techniques to address this flaw. It also presents an effective method for tackling completely membership-based neutrosophic linear programming problems. The computational complexity of the proposed method is lower than the one of some other popular methods from the specialized literature.

The following is a summary of the contributions made by this study:

1. Introducing a direct method to solve FNLP problems.
2. Keeping the NLP problem's structure intact for ease of solution and implementation.
3. Dealing with indeterminacy in a completely independent manner using NSs.

The remaining sections are organized as follows: Section 2 provides the operational concepts of SVNSs as well as some other important ideas. Section 3 offers a novel way of determining the best answer to NLP challenges. In Section 4, a numerical example is provided to clarify the proposed method. Section 5 discusses the benefits of the technique proposed in the current work. The conclusion of the investigation is presented in section 6.

2. Preliminaries

This part reviews some definitions and preliminary information on NSs, SVNSs, and other vital features.

Definition 1. (Nafei, Gu &Yuan, 2021) Assume that X is a domain. In a SVNS, U through X is taking the form $U = \{x, T_U(x), I_U(x), F_U(x); x \in X\}$, where $T_U(x), I_U(x), F_U(x): X \to [0,1]$, and $0 \le T_U(x) + I_U(x) + F_U(x) \le 3$ for all $x \in X$. $T_U(x), I_U(x)$ and $F_U(x)$ represent the truth membership degree, the indeterminacy membership degree, and the falsity membership degree, respectively, of x to U.

Remark: The trinary $(T_N(x), I_N(x), F_N(x))$ is known as SVNN. Conveniently, this trinary is frequently symbolized by (T, I, F).

Definition 2. (Smarandache & Abdel-Basset, 2020) Assume that $x = (T_1, I_1, F_1)$ and $y = (T_2, I_2, F_2)$ are SVNNs. The arithmetic operations between x and y are defined as follows:

$$x \oplus y = \left(T_1 + T_2 - T_1T_2, I_1I_2, F_1F_2\right), \tag{1}$$

$$x \otimes y = \begin{pmatrix} T_1T_2, I_1 + I_2 - I_1I_2, \\ F_1 + F_2 - F_1F_2 \end{pmatrix}, \tag{2}$$

$$\lambda x = \left(1-(1-T_1)^{\lambda}, I_1^{\lambda}, F_1^{\lambda}\right), \tag{3}$$

$$x^{\lambda} = \left(T_1^{\lambda}, 1-(1-I_1)^{\lambda}, 1-(1-F_1)^{\lambda}\right), \quad \lambda > 0. \tag{4}$$

$$x \overset{N}{-} y = \left(\frac{T_1 - T_2}{1-T_2}, \frac{I_1}{I_2}, \frac{F_1}{F_2}\right),$$

$$x \overset{N}{\div} y = \left(\frac{T_1}{T_2}, \frac{I_1 - I_2}{1-I_2}, \frac{F_1 - F_2}{1-F_2}\right).$$

Definition 3. (Nafei, Yuan & Nasseri, 2020) Assume that U and V are two NSs. For all $x \in X$, U is included in V, if and only if:

$$\begin{aligned} &Sup\ I_U(x) \geq Sup\ I_V(x), \\ &Inf\ I_U(x) \geq Inf\ I_V(x), \\ &Inf\ T_U(x) \leq Inf\ T_V(x), \\ &Sup\ T_U(x) \leq Sup\ T_V(x), \\ &Sup\ F_U(x) \geq Sup\ F_V(x), \\ &Inf\ F_U(x) \geq Inf\ F_V(x). \end{aligned} \tag{5}$$

Definition 4. (Smarandache & Abdel-Basset, 2021) Let U be a NS. The complement of U is interpreted by U^c, and it could be defined as $T_U^c(x) = \{1^+\} - T_U(x), I_U^c(x) = \{1^+\} - I_U(x)$, $F_U^c(x) = \{1^+\} - F_U(x). \forall x \in X$. Therefore, $U^c = \{x, F_U(x), 1 - I_U(x), T_U(x); x \in X\}$.

3. The Proposed Method

LP, which copes with linear objective functions and constraints, is useful for obtaining the best optimal mathematical modeling solution. The strategy used in most of the existing methods is the employment of a ranking function used to convert neutrosophic numbers to real numbers. Assume that A and B are two different SVNNs, and R is a sorting factor for arranging the Neutrosophic Numbers (NNs). In this instance, if $R(A) = R(B)$ then $A = B$, which is not always true. In such circumstances, alternative ranking functions must be used (Smarandache, 2020). In addition, by getting the ideal answer as a crisp number, the levels of truthfulness, indeterminacy, and falsehood cannot be accurately comprehended in the final solution.

Also, no technique for solving fully neutrosophic problems has been proposed. In order to overcome these shortcomings, this section describes a novel process for addressing the fully membership-based neutrosophic linear programming problems. This research work proposes a direct technique for solving the NLP problems without a ranking function. A fully membership-based neutrosophic linear programming problem can be written as follows:

$$\begin{aligned} &Max\ Z = \sum_{j=1}^{n} \tilde{c}_j \tilde{x}_j, \\ &s.t. \\ &\sum_{j=1}^{n} \tilde{a}_{ij} \tilde{x}_j \lesssim \tilde{b}_i, \\ &\tilde{x}_j \gtrsim 0.\ i = 1,\dots,m,\ j = 1,\dots,n \end{aligned} \tag{6}$$

where $\tilde{c}_j, \tilde{x}_j, \tilde{a}_{ij}$ and $\tilde{b}_i$ are neutrosophic numbers that can be demonstrated as: $\tilde{c}_j = (c_j^T, c_j^I, c_j^F)$, $\tilde{x}_j = (x_j^T, x_j^I, x_j^F)$, $\tilde{a}_{ij} = (a_{ij}^T, a_{ij}^I, a_{ij}^F)$, and $\tilde{b}_i = (b_i^T, b_i^I, b_i^F)$. The algorithm of the suggested approach is outlined below.

Algorithm

Step 1. Rewrite problem (6) as follows:

$$\begin{aligned} &Max\ Z = \sum_{j=1}^{n} (c_j^T, c_j^I, c_j^F)(x_j^T, x_j^I, x_j^F), \\ &s.t. \\ &\sum_{j=1}^{n} (a_{ij}^T, a_{ij}^I, a_{ij}^F)(x_j^T, x_j^I, x_j^F) \lesssim (b_i^T, b_i^I, b_i^F), \\ &0 \leq x_j^T, x_j^I, x_j^F \leq 1,\ i = 1,\dots,m,\ j = 1,\dots,n. \end{aligned} \tag{7}$$

Step 2. Without loss of generality, the previous problem can be considered as a crisp multi-objective linear programming problem with three objective functions as follows:

$$\begin{aligned} &Max \sum_{j=1}^{n} c_j^T x_j^T, Max \sum_{j=1}^{n} c_j^I x_j^I, Max \sum_{j=1}^{n} c_j^F x_j^F, \\ &s.t. \\ &\sum_{j=1}^{n} a_{ij}^T x_j^T \lesssim b_i^T, \\ &\sum_{j=1}^{n} a_{ij}^I x_j^I \lesssim b_i^I, \\ &\sum_{j=1}^{n} a_{ij}^F x_j^F \lesssim b_i^F, \\ &0 \leq x_j^T, x_j^I, x_j^F \leq 1,\ i = 1,\dots,m,\ j = 1,\dots,n. \end{aligned} \tag{8}$$

Step 3. Regarding equation (8), the optimal solution of the following crisp model is firstly obtained:

$$\begin{aligned} & Max \sum_{j=1}^{n} c_j^T x_j^T, \\ & s.t. \\ & \sum_{j=1}^{n} a_{ij}^T x_j^T \lesssim b_i^T, \\ & 0 \le x_j^T \le 1,\ i = 1,\dots,m,\ j = 1,\dots,n. \end{aligned} \tag{9}$$

The above problem is a crisp one and it can be solved using a standard simplex algorithm. The obtained optimal solution $(x_j^*)^T$ gives the truth-values of the neutrosophic optimal solution of the problem (7).

Step 4. To find the median value of the neutrosophic optimal solution of problem (7), the following crisp problem needs to be solved.

$$\begin{aligned} & Max \sum_{j=1}^{n} c_j^I x_j^I, \\ & s.t. \\ & \sum_{j=1}^{n} a_{ij}^I x_j^I \lesssim b_i^I, \\ & 0 \le x_j^I \le 1,\ i = 1,\dots,m,\ j = 1,\dots,n. \end{aligned} \tag{10}$$

The obtained optimal solution $(x_j^*)^I$ gives the indeterminacy values of the neutrosophic optimal solution of problem (7).

Step 5. To obtain the right point of the neutrosophic optimal solution of problem (7), one has:

$$\begin{aligned} & Max \sum_{j=1}^{n} c_j^I x_j^I, \\ & s.t. \\ & \sum_{j=1}^{n} a_{ij}^I x_j^I \lesssim b_i^I, \\ & 0 \le x_j^I \le 1,\ i = 1,\dots,m,\ j = 1,\dots,n. \end{aligned} \tag{11}$$

Similarly, the optimal solution of the previous problem can be obtained using the standard simplex approach. The obtained optimal solution $(x_j^*)^F$ gives the falsity-values of the neutrosophic ideal solution of problem (7).

Step 6. By applying the obtained optimal solution $\tilde{x}_j^* = ((\tilde{x}_j^*)^T, (\tilde{x}_j^*)^I, (\tilde{x}_j^*)^F)$ in the objective function of problem (7), and by using the neutrosophic operators presented in equation (2), the optimal value of neutrosophic problem can be obtained as follows:

$$\tilde{c}_j \tilde{x}_j^* = \sum_{j=1}^{n} (c_j^T, c_j^I, c_j^F) \otimes ((\tilde{x}_j^*)^T, (\tilde{x}_j^*)^I, (\tilde{x}_j^*)^F) \tag{12}$$

Figure 2 depicts the workflow of the suggested technique.

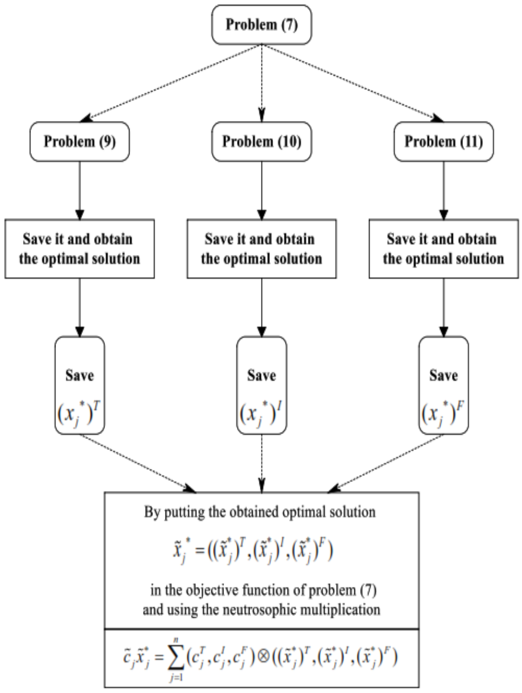

Figure 2. The flowchart of the suggested technique

4. Numerical Illustration

A mobile factory produces three basic units: Cameras, Speakers, and Rams. All products must undergo three stages. "Design," "Fabrication," and "Probe" are considered the phases of production. Due to the advantages of neutrosophic sets, decision-makers have been asked to provide the corresponding values with respect to neutrosophic numbers. Table 1 shows the reasonable price for each unit produced as well as the profit. The corporation intends to develop items within this constraint in order to maximize attainable profits. This problem may be stated as follows:

$$\begin{aligned}
&Max\ \tilde{Z} = (0.2, 0.5, 0.9)\tilde{x}_1 \oplus (0.6, 0.7, 0.9)\tilde{x}_2 \\
&\oplus (0, 0.5, 1)\tilde{x}_3 \\
&s.t. \\
&(0.2, 0.7, 1)\tilde{x}_1 \oplus (0.6, 0.7, 0.9)\tilde{x}_2 \oplus \\
&(0.2, 0.3, 0.4)\tilde{x}_3 \tilde{\leq} (0.9, 0, 8, 0.6), \\
&(0.5, 0.7, 0.8)\tilde{x}_2 \oplus (0.2, 0.7, 0.9)\tilde{x}_3 \tilde{\leq} \\
&(0.8, 0.8, 0.4), \\
&(0.2, 0.6, 0.9)\tilde{x}_1 \oplus (0.1, 0.4, 0.9)\tilde{x}_3 \tilde{\leq} \\
&(1, 0.6, 0.7), \\
&0 \leq \tilde{x}_j \leq 1,\ \ j = 1, 2, ..., 3.
\end{aligned} \tag{13}$$

The preceding issue may be transformed into the following equations using problem (6):

$$\begin{aligned}
&Max\ \tilde{Z} = (0.2, 0.5, 0.9)(x_1^T, x_1^I, x_1^F) \oplus \\
&(0.6, 0.7, 0.9)(x_2^T, x_2^I, x_2^F) \oplus \\
&(0, 0.5, 1)(x_3^T, x_3^I, x_3^F), \\
&s.t. \\
&(0.2, 0.7, 1)(x_1^T, x_1^I, x_1^F) \oplus \\
&(0.6, 0.7, 0.9)(x_2^T, x_2^I, x_2^F) \oplus \\
&(0.2, 0.3, 0.4)(x_3^T, x_3^I, x_3^F) \tilde{\leq} \\
&(0.9, 0, 8, 0.6), \\
&(0.5, 0.7, 0.8)(x_2^T, x_2^I, x_2^F) \oplus \\
&(0.2, 0.7, 0.9)(x_3^T, x_3^I, x_3^F) \tilde{\leq} \\
&(0.8, 0.8, 0.4), \\
&(0.2, 0.6, 0.9)(x_1^T, x_1^I, x_1^F) \oplus \\
&(0.1, 0.4, 0.9)(x_3^T, x_3^I, x_3^F) \tilde{\leq} \\
&(1, 0.6, 0.7), \\
&0 \leq x_j^T, x_j^I, x_j^F \leq 1,\ \ j = 1, ..., 3.
\end{aligned} \tag{14}$$

Based on problem (7), this problem can be converted into the following form:

$$\begin{aligned}
&Max(0.2x_1^T + 0.6x_2^T) \\
&Max(0.5x_1^I + 0.7x_2^I + 0.5x_3^I) \\
&Max(0.9x_1^F + 0.9x_2^F + 1x_3^F) \\
&s.t. \\
&(0.2x_1^T + 0.6x_2^T + 0.2x_3^T) \leq 0.9, \\
&(0.7x_1^I + 0.7x_2^I + 0.3x_3^I) \leq 0.8, \\
&(1x_1^F + 0.9x_2^F + 0.4x_3^F) \leq 0.6, \\
&(0.5x_2^T + 0.2x_3^T) \leq 0.8, \\
&(0.7x_2^I + 0.7x_3^I) \leq 0.8, \\
&(0.8x_2^F + 0.9x_3^F) \leq 0.4, \\
&(0.2x_1^T + 0.1x_3^T) \leq 1, \\
&(0.6x_1^I + 0.4x_3^I,) \leq 0.6, \\
&(0.9x_1^F + 0.9x_3^F) \leq 0.7, \\
&0 \leq x_j^T, x_j^I, x_j^F \leq 1,\ \ j = 1, ..., 3.
\end{aligned} \tag{15}$$

Based on problem (9), to obtain the truth-values of the neutrosophic optimal solution of problem (13), $((x_j^*)^T, j = 1, 2, 3)$, one has:

$$\begin{aligned}
&Max(0.2x_1^T + 0.6x_2^T) \\
&s.t. \\
&(0.2x_1^T + 0.6x_2^T + 0.2x_3^T) \leq 0.9 \\
&(0.5x_2^T + 0.2x_3^T) \leq 0.8 \\
&(0.2x_1^T + 0.1x_3^T) \leq 1 \\
&0 \leq x_1^T, x_2^T, x_3^T \leq 1
\end{aligned} \tag{16}$$

By solving the crisp linear problem (16) using the primal simplex algorithm, the following values are obtained: $(x_1^*)^T = 1, (x_2^*)^T = 1, (x_3^*)^T = 0$ and

$$Z^* = 0.8. \tag{17}$$

Table 1. Departments and profits

Products Profit	Design	Fabrication	Probe	Unit
P_1	(0.2,0.7,1.0)	(0.0,0,0,0.0)	(0.2,0.6,0.9)	(0.2,0.5,0.9)
P_2	(0.6,0.7,0.9)	(0.5,0.7,0.8)	(0.0,0,0,0.0)	(0.6,0.7,0.9)
P_3	(0.2,0.3,0.4)	(0.2,0.7,0.9)	(0.1,0.4,0.9)	(0.0,0.5,1.0)
Capacity	(0.9,0.8,0.6)	(0.8,0.8,0.4)	(1.0,0.6,0.7)	

Now, intending to find the indeterminacy-values of the neutrosophic optimal solution of problem (13), i.e., $((x_j^*)^I, j=1,2,3)$, one has:

$$\begin{aligned} & Max(0.5x_1^I + 0.7x_2^I + 0.5x_3^I) \\ & s.t. \\ & (0.7x_1^I + 0.7x_2^I + 0.3x_3^I) \le 0.8 \\ & (0.7x_2^I + 0.7x_3^I) \le 0.8 \\ & (0.6x_1^I + 0.4x_3^I,) \le 0.6 \\ & 0 \le x_1^I, x_2^I, x_3^I \le 1 \end{aligned} \tag{18}$$

Using the primal simplex algorithm, the optimal solutions and optimal value are obtained as follows:

$$(x_1^*)^I = 0.46, (x_2^*)^I = 0.34, (x_3^*)^I = 0.81$$

and

$$Z^* = 0.86923077. \tag{19}$$

Finally, the following LP problem is solved to find the falsity-values of the neutrosophic optimal solution of problem (13), i.e. $((x_j^*)^F, j=1,2,3)$.

$$\begin{aligned} & Max(0.9x_1^F + 0.9x_2^F + 1x_3^F) \\ & s.t. \\ & (1x_1^F + 0.9x_2^F + 0.4x_3^F) \le 0.6, \\ & (0.8x_2^F + 0.9x_3^F) \le 0.4, \\ & (0.9x_1^F + 0.9x_3^F) \le 0.7, \\ & 0 \le x_1^F, x_2^F, x_3^F \le 1. \end{aligned} \tag{20}$$

Using the primal simplex algorithm, the optimal solutions and optimal value are obtained as follows:

$$(x_1^*)^F = 0.39, (x_2^*)^F = 0.06, (x_3^*)^F = 0.39,$$

and (21)

$$Z^* = 0.79474591.$$

Finally, based on the optimal solutions obtained in (17), (19), and (21), the neutrosophic optimal solutions of NLP (13) are obtained as follows:

$$\tilde{x}_j^* = \begin{pmatrix} ((x_1^*)^T, (x_1^*)^I, (x_1^*)^F) = (1, 0.46, 0.39) \\ ((x_2^*)^T, (x_2^*)^I, (x_2^*)^F) = (1, 0.34, 0.06) \\ ((x_3^*)^T, (x_3^*)^I, (x_3^*)^F)) = (0, 0.81, 0.39) \end{pmatrix}.$$

Equivalently, using the mathematical operations for single-valued neutrosophic numbers, the objective value of NLP is obtained as follows:

$$\sum_{j=1}^{3} \tilde{c}_j \otimes \tilde{x}_j^{\,*} = 2.468.$$

5. Comparisons Between the Proposed Approach and Other Existing Approaches

By comparing the proposed method with the score function-based method proposed by (Abdel-Basset et al., 2019) on the same problem, it can be observed that:

1. The method proposed in this paper is able to solve Membership-based Neutrosophic Linear Programming (MNLP) problems, while the previous method cannot solve it.

2. By using the proposed strategy, the NLP pro lems (problems with non-deterministic variables) can be completely solved, in contrast with the Neuromorphic usage of their method that cannot handle this kind of problem.

3. The results of the proposed method are better than their results. As shown in the previous section, the optimal value obtained when employing the method proposed in this paper is equal to 2.468, while the optimal value obtained when employing their method is equal to 0.588.

4. When introducing, in the proposed method, a direct strategy to completely solve the NLP problems, the structure of the NLP problem was kept intact, for ease of solution and implementation.

Also, by comparing the method proposed in this paper with the method proposed by Nancy & Garg (2016), for solving the same problem, it can be observed that:

1. The score function used in the method proposed by Nancy & Garg (2016) has deficiencies in ranking numbers in some special situations (Nafei et al., 2021), which causes a negative impact on the final optimal value. In contrast, the direct character of the proposed method excludes it from this shortcoming.

2. The optimal value obtained when using the method proposed by Nancy & Garg (2016) is equal to 1.23, a value which is almost half of the one obtained when using the proposed method.

3. Unlike the method proposed by Nancy & Garg (2016), the proposed method can solve NLP problems with neutrosophic values for variables.

Finally, by comparing the method proposed in this paper with the method proposed by Dubei & Mehra (2011), for solving the same problem, it can be observed that:

1. Because all the components of the decision-making system are incorporated within the proposed analyses (i.e., the truthfulness, the indeterminacy, and the falsity degree), the proposed approach matches the reality with more accuracy, in comparison with the method proposed by Dubei & Mehra (2011).

2. The optimal value obtained when using the method proposed by Dubei & Mehra (2011) is equal to 2.4. This optimal value is almost equal to the one obtained when using the proposed method.

3. In the proposed method, indeterminacy is considered an independent element. In contrast, the method proposed by Dubei & Mehra (2011) is unable to independently address indeterminacy.

6. Conclusion

As a form of mathematical optimization, LP is a powerful technique for finding the best way to use the limited resources needed to obtain a given objective. Because many actual concerns have become too complicated to be characterized precisely, indeterminacy is frequently present in almost any engineering planning process. As an application of FS and IFS, Neutrosophic is useful in coping with ambiguities. In this paper, for the first time, a linear programming problem with membership-based neutrosophic numbers is taken into consideration. To present an efficient method for solving fully membership-based NLP problems, this research proposes a new technique for converting the NLP problems into three crisp problems and then for solving them using the existing standard methods. Finally, this method is entirely applied to the problem of selecting processors in the mobile phone industry and compared with several other given methods. The validity and reliability of the approach proposed in this method are verified. Unlike other existing methods, the proposed method can solve NLP problems with neutrosophic values for variables. In the research presented in this paper, the decision-makers have the freedom to consider the variables with neutrosophic structure, while obtaining the optimal objective value as a crisp number. Moreover, the proposed method will help to study some concepts of LP, to investigate duality results, and to be more critical in the sensitivity analysis. In the future, an optimized strategy for solving decision-making methods based on neutrosophic values will be presented.

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