



Research Article

# A novel neutrosophic fuzzy programming model for multiobjective transportation problems with survival costs

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## ABSTRACT

This study proposes a novel neutrosophic fuzzy programming framework for solving multiobjective transportation problems (MOTPs) with a time-dependent survival cost function. The proposed model integrates parabolic fuzzy parameters with a neutrosophic compromise programming approach (NCPA) to manage uncertainty, indeterminacy, and imprecise information in decision-making. The inclusion of survival cost functions enables the model to capture the probabilistic nature of transportation reliability under fluctuating supply and demand conditions. The fuzzy model is transformed into an equivalent deterministic form using de-fuzzification, and the neutrosophic framework is subsequently applied to derive a compromise solution. A real-life case study in pharmaceutical logistics demonstrates the practical relevance of the model. It highlights its capability to generate more stable and balanced results compared to classical fuzzy programming. The findings suggest that neutrosophic programming provides a more comprehensive decision-support mechanism for MOTPs operating under uncertainty.

## 1. Introduction

Mathematical programming utilizes linear programming problems (LPPs), which are widely recognized for their extensive application in numerous fields. Transportation problem (TP) is one of the fundamental optimization fields that fall within these applications. The TP is essential in logistics, supply chain, and supplier selection processes. Using a single objective to optimize TPs fails to deliver the best results when operating in highly competitive markets. Decision-makers (DMs) face situations that require analyzing numerous contradictory objectives, resulting in multi-objective transportation problems (MOTPs). The traditional MOTPs use linear objective functions, yet specific practical applications necessitate working with nonlinear functions. Introducing non-linearity into models delivers enhanced results that better serve the DM's strategic choices when circumstances demand it.

Hitchcock (1941a) was the first to introduce the TP as a mathematical form. Later, Hitchcock (1941b) proposed a TP with nonlinear costs that was formulated and solved, thereby initiating a surge of research in this domain. A supply chain problem is considered incomplete without incorporating a transportation aspect. Many innovative concepts and mathematical techniques have been developed to address TPs in recent years. Akdemir and Tiryaki (2012) proposed a bi-level stochastic TP model, which optimizes transportation with stochastic demand in decentralized firms. Roy et al. (2012) proposed a technique for transforming cost coefficients with multiple choices or goals was proposed. Furthermore, a multi-choice stochastic TP with an exponential distribution was introduced. This problem was designed to address real-world transportation challenges involving uncertain

factors. Javaid et al. (2013) presented a multipurpose bottleneck TP that is expanded to include randomness and flexibility in supply and demand. Moreover, a bi-criteria stochastic problem was also developed. Xu and Huang (2013) provided a new modeling approach to the traveling salesman problem (TSP) for the context of a transportation hotspot market for multiple bilateral swaps. This method examines the TSP considering a stochastic demand periodic sealed double auction. Rani and Gulati (2014) introduced an innovative approach to tackle the challenges of unbalanced TP. Quddoos et al. (2014) proposed a general form of multi-criteria stochastic TP with the equivalent deterministic model. Roy (2016) introduced Lagrange's interpolating polynomial, which is used to minimize total cost. It also presents a method for transforming stochastic supply constraints into deterministic constraints using stochastic programming. Abdel-Basset et al. (2019) proposed a method for solving the neutrosophic linear programming models, whose parameters are represented by trapezoidal neutrosophic numbers. Angelov (1997) introduced the optimization method for the first time in an intuitionistic framework. Mahmoodirad et al. (2019) suggested a novel, efficient method for resolving the TPs by treating all parameters as triangular intuitionistic fuzzy values. Kour and Basu (2015) recommended using the extended fuzzy programming problem in a neutrosophic environment for real-world MOTPs.

Rizk-Allah et al. (2018) solved the MOTPs in a neutrosophic setting and used the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methodology to measure the ranking degree to compare the findings with previous methods. Melethil et al. (2025) implemented neutrosophic programming in enhancing the state of Canada towards the achievement of Sustainable Development Goals

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(SDGs), noting that Canada has faced diverse difficulties in promoting sustainable economic development alongside sustainable development; they also noted uncertainties involved in decision-making systems. Ahmad and Adhami (2019) studied TPs that incorporate uncertainty using interval-based optimization, time-dependent cost functions, and probabilistic models, enhancing decision-making through robust mathematical and multiobjective optimization approaches. Ge and Ishii (2011) introduced the suggested bottleneck TP. Moreover, by integrating the assemblage of both the flexible supply side and the demand side, a new bi-directional stochastic criterion problem was produced as an extension towards overcoming the limitations of the bottleneck transit issue.

Adhami et al. (2022) proposed a neutrosophic compromise programming approach (NCPA) as the best compromise solution for the TP, which focused on uncertainties in multi-objective TPs and addressed fuzzy and stochastic parameter uncertainties efficiently. Biswas et al. (2019) investigated both crisp and interval settings in a multi-objective fixed-charge TP. Gupta et al. (2020b) proposed a multi-objective TP with capacitated restrictions. It assumes that the parameter of supply and demand follows a gamma distribution. Gupta et al. (2020a) conducted a case study on the issue of capacitated transportation difficulties with multiple objectives in an unpredictable setting. Soroush et al. (2020) studied problems associated with the transportation and inventory of maritime goods under three distinct daily demand scenarios. The research employs computational analysis to investigate the impact of gamma, exponential, and uniform demand patterns on the observed outcomes. Agrawal and Ganesh (2020) outlined a method to solve the resolution of fuzzy fractional TPs with stochastic exponential distribution parameter using fuzzy random variables (RVs), dual approach, and fuzzy programming to solve for the solutions. (Giri & Roy, 2024) proposed a fuzzy-random robust flexible programming model for a sustainable closed-loop renewable energy supply chain integrating PV, biogas, and incineration systems, offering optimized facility selection and reduced environmental impact under uncertainty. (Giri & Roy, 2025) proposed a distributionally robust, multi-objective conic goal programming model for India's closed-loop hydrogen and energy network, demonstrating reduced emissions, improved waste utilization, and enhanced operational efficiency across integrated gas and electricity systems.

## 2. Literature review and thematic classification

To handle many sources of uncertainty, recent research on transportation optimization has moved from deterministic to stochastic, fuzzy, intuitionistic, and neutrosophic modelling frameworks. This evolution is summed up in the thematic synthesis that follows.

### 2.1 Stochastic approaches

Several researchers have incorporated randomness into transportation models. Akdemir and Tiryaki (2012) developed a bi-level stochastic TP model with exponentially distributed demand, while Roy et al. (2012) formulated a multi-choice stochastic TP based on exponential distribution. Ahmad and Adhami (2019) introduced probabilistic cost functions under varying supply and demand, showing that stochastic modeling improves decision reliability.

### 2.2 Fuzzy and intuitionistic approaches

Fuzzy theory has been widely used to model imprecision in transportation parameters. Mahmoodirad et al. (2019) and Rani and Gulati (2014) applied fuzzy and intuitionistic fuzzy techniques for transportation decision-making with imprecise cost and demand data. Kour and Basu (2015) extended fuzzy programming to neutrosophic environments, while Angelov (1997) first introduced optimization in an intuitionistic fuzzy framework. These works improve flexibility but cannot explicitly quantify indeterminacy or conflicting information.

### 2.3 Neutrosophic approaches

Abdel-Basset et al. (2019) presented a fully neutrosophic linear programming model using trapezoidal neutrosophic numbers, addressing

truth, indeterminacy, and falsity degrees. Rizk-Allah et al. (2018) developed a multiobjective transportation model under a neutrosophic environment using the TOPSIS ranking method. Adhami et al. (2022) proposed an NCPA for multiobjective nonlinear TPs considering an exponential distribution. Although these studies significantly advanced neutrosophic optimization, they do not incorporate time-dependent survival cost functions, which play a critical role in logistics reliability.

Most of these studies are descriptive in nature and do not investigate how their assumptions affect real-world performance, despite the fact that they significantly improved uncertainty modeling in TPs. While fuzzy and intuitionistic approaches capture imprecision but are unable to explicitly quantify indeterminacy or contradictory information, stochastic models mainly address randomness but are unable to represent vagueness. The Truth, Indeterminacy, and Falsity structure is included in current neutrosophic models, but they typically ignore survival-based cost functions and time-dependent variability. These drawbacks emphasize the need for a single framework that can represent fuzziness, indeterminacy, and time-dependent uncertainty all at once.

### 2.4 Comparison with key existing models

The proposed framework is different from significant previous research in a number of ways. Neutrosophic linear programming was introduced by Abdel-Basset et al. (2019), but fuzzy parabolic parameters and survival cost functions were not included. Although Rizk-Allah et al. (2018) used neutrosophic TOPSIS for MOTPs, their model did not take time-dependent costs into account and lacked a hybrid fuzzy-neutrosophic structure. An NCPA was developed by Adhami et al. (2022), but its applicability to reliability-sensitive logistics systems is limited due to the lack of parabolic fuzzy numbers and survival probability. The current study offers a more comprehensive and practically applicable decision-support model by incorporating these lacking elements.

### 2.5 Research gap and contributions

From the thematic synthesis above, it is evident that while fuzzy, intuitionistic, and neutrosophic approaches have improved uncertainty modeling in TPs, no existing framework simultaneously integrates parabolic fuzzy parameters, survival cost functions, and neutrosophic compromise programming. This omission limits their ability to represent real-world cost variability due to time delays, product perishability, and delivery risks.

To bridge this gap, the present study:

- Formulates a neutrosophic fuzzy programming model that integrates time-dependent survival cost functions into multiobjective TPs.
- Employs parabolic fuzzy numbers to model uncertain parameters and transforms them into deterministic equivalents.
- Uses neutrosophic membership functions (truth, indeterminacy, and falsity) to capture ambiguity and inconsistency in decision-making.

This contribution extends the prior works of Abdel-Basset et al. (2019), Rizk-Allah et al. (2018), and Adhami et al. (2022) by combining their theoretical insights with a survival-cost-based neutrosophic framework that offers enhanced interpretability and stability.

All these contributions fill in the major methodological gaps in earlier studies. The proposed framework simultaneously integrates survival cost, parabolic fuzzy parameters, and neutrosophic compromise programming, in contrast to previous studies on stochastic, fuzzy, intuitionistic, and neutrosophic approaches. In MOTPs, this integrated structure enhances the model's robustness and stability by more effectively capturing time-dependent variability, imprecise judgments, and uncertain information.

## 3. Fuzzy set (FS)

A fuzzy set  $X$  within a universe  $W$ , where each element is denoted by  $w$ , is characterized by a membership function  $\mu_X(w)$  that maps

elements from  $W$  to the interval  $[0,1]$ . This function assigns to each element  $w \in W$  a membership degree  $\mu_X(w) \in [0,1]$ , indicating the extent of  $w$ 's membership in the fuzzy set  $X$ . Specifically,  $\mu_X(w) = 0$  signifies that  $w$  is not a member of  $X$ ,  $\mu_X(w) = 1$  indicates full membership, and values between 0 and 1 represent partial membership.

A parabolic fuzzy number is a triplet  $X(x,y,z)$  that represents the smallest, middle, and greatest values of a membership function if its membership function is specified as follows:

$$\mu_X(v) = \begin{cases} \left(\frac{v-x}{y-x}\right)^2, & \text{if } x \leq v \leq y; \\ 1, & \text{if } v = y; \\ \left(\frac{z-v}{z-y}\right)^2, & \text{if } y < v \leq z; \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

For the parabolic fuzzy number  $\tilde{X}(x,y,z)$ , the de-fuzzified value function  $d$  may be written as follows:

$$d(\tilde{X}) = \frac{x+2y+z}{4} \tag{2}$$

#### 4. Intuitionistic fuzzy set (IFS)

##### 4.1 Definition

**Smarandache (2019)** Let  $V$  be a discourse universe. The ordered triplets constitute an IFS  $X$  in  $V$ :

$$X = \{v, \mu_X(v), \nu_X(v) | v \in V\} \tag{3}$$

The degrees of membership and non-membership of  $v$  in  $X$  are represented by the membership function  $\mu_X(v): V \rightarrow [0,1]$  and the non-membership function  $\nu_X(v): V \rightarrow [0,1]$  associated with each element  $v \in V$  in an intuitionistic fuzzy set  $X$  over the universe  $V$ . The following criteria is met by IFS's membership and non-membership functions:

$$0 \leq \mu_X(v) + \nu_X(v) \leq 1 \tag{4}$$

##### 4.2 Optimization with IFS

For the multi-objective optimization problem, the objective is to maximize the function  $\lambda - \Gamma$ , subject to the following constraints:

$$\mu_k(x) \leq \lambda, \quad \nu_k(x) \leq \Gamma, \quad \lambda \geq \Gamma \geq 0 \tag{5}$$

#### 5. Neutrosophic set (NS)

##### 5.1 Definition

According to **Smarandache (1999)**, a neutrosophic set  $B$  in a universe of discourse  $Z$  is defined for each element  $z \in Z$  by three membership functions: truth  $R_B(z)$ , indeterminacy  $L_B(z)$ , and falsity  $G_B(z)$ .

$$B = \{z, R_B(z), L_B(z), G_B(z) | z \in Z\} \tag{6}$$

$R_B(z)$ ,  $L_B(z)$ , and  $G_B(z)$  represent real standard or non-standard subsets in the range  $]0^-, 1^+[$ :

$$R_B(z) \rightarrow ]0^-, 1^+[ , \quad L_B(z) \rightarrow ]0^-, 1^+[ , \quad G_B(z) \rightarrow ]0^-, 1^+[$$

Since the total of  $R_B(z)$ ,  $L_B(z)$ , and  $G_B(z)$  is unconstrained, the connection is as follows:

$$0^- \leq \sup R_B(z) + L_B(z) + G_B(z) \leq 3^+ \tag{7}$$

##### 5.2 Definition

**(Smarandache (1999))** The union of  $B$  and  $C$ , or  $D = (B \cup C)$ , is also a single-valued neutrosophic set (SVNS)  $D$  given two SVNSs  $B$  and  $C$ . Its membership functions for truth  $R_D(z)$ , indeterminacy  $L_D(z)$ , and falsity  $G_D(z)$  are as follows:

$$\begin{aligned} R_D(z) &= \max(R_B(z), R_C(z)) \\ L_D(z) &= \max(L_B(z), L_C(z)) \\ G_D(z) &= \min(G_B(z), G_C(z)) \quad \text{for each } z \in Z. \end{aligned}$$

#### 6. Transportation optimization with survival cost functions under fluctuating supply and demand

The normal day is significantly impacted by TPs. There are often objectives to meet when delivering partnerships or products. Understanding the optimal outcomes in real-world scenarios with relation to goal functions requires modeling and optimizing TPs under specific restrictions. When homogeneous commodities or products must be transported from different origins (or warehouses) to different sinks (or markets) at the lowest possible cost, in the shortest amount of time, or in order to optimize profit, among other limitations, this is referred to as a TPs.

Finding the total number of goods that must be delivered in order to achieve the recommended ideal goals is the goal.

Imagine a TP in which  $I$  origins have a supply of  $s_i$  units ( $i = 1, 2, \dots, I$ ) and  $J$  destinations have a demand for  $d_j$  units ( $j = 1, 2, \dots, J$ ). The cost of moving one unit from the  $i$ -th origin to the  $j$ -th destination is represented by  $r_{ij}$ .

To find the optimal solution, the decision variable  $y_{ij}$  denotes the unknown number of units moved from the  $i$ -th origin to the  $j$ -th destination.

Now, the general mathematical model for TPs is given by

##### Model 1

$$Z = \sum_{i=1}^I \sum_{j=1}^J \left( \frac{r_{ij}}{q_{ij}} \right) y_{ij}$$

Subject to:

$$\sum_{j=1}^J y_{ij} \leq s_i, \quad i = 1, 2, \dots, I \tag{8}$$

$$\sum_{i=1}^I y_{ij} \geq d_j, \quad j = 1, 2, \dots, J$$

$$y_{ij} \geq 0, \quad \forall i, j$$

In most TPs, it is anticipated that the items will be delivered within the allotted period. Additional penalties, such as product damage or customer order cancellations owing to delays or lost time, may be levied if this requirement is not fulfilled. The distributor's or transporter's reputation may suffer because of these sanctions. Road conditions, traffic, weather, and other environmental factors are just a few of the variables that can affect the transportation system and result in product delivery delays. The earnings and transportation expenses might no longer be regarded as fixed values in such situations. **Maity et al. (2016)**

introduced the concept of ‘Survival cost/profit,’ which is a probabilistic function of the cost and profit in the proposed study.

**7. Survival function**

In logistics, survival cost/profit is the likelihood that a product will be successfully transported and delivered within the specified time, subject to the constraints imposed by DMs. The fixed cost rises and the fixed profit falls when probabilistic cost is incorporated into TPs. This has a substantial effect on the profit made from these items/products and changes the initial value of the goods being delivered. This is the definition of the cost/profit probability function,  $\Psi_{ij}(t)$ , which is dependent on time  $t$ :

$$\Psi_{ij}(t) = \frac{\text{quantity of items that are still in good shape following delays in transit}}{\text{Total quantity of cargo shipped}}$$

Likewise, the likelihood of failure,  $F_{ij}(t)$ , can be given as:

$$F_{ij}(t) = \frac{\text{quantity of products harmed as a result of late or delayed shipment}}{\text{Total quantity of cargo shipped}}$$

These probabilities satisfy the following equation:

$$\Psi_{ij}(t) + F_{ij}(t) = 1 \tag{9}$$

The practical observation that delays, decay, and real-time disruptions directly impact transportation reliability is what drives the use of survival cost functions. The chance that a shipment will arrive at its destination within the allowed time frame is reflected in the survival probability. These probabilities are usually estimated using managerial expectations, past delivery performance, or expert judgment because historical data is frequently limited. DMs can explicitly account for risk and rapid losses that traditional fuzzy and neutrosophic models ignore by incorporating survival probability into the model.

The basic objective functions of profit and cost are changed into survival profit and survival cost when time is included as a factor, enabling the model to take delays and their effects into consideration. Determining whether the main goal should be to minimize total transportation cost or maximize overall profit is a significant difficulty in this approach (Maity et al., 2016).

**Case 1:** In the event that the objective is to minimize transportation costs, the survival cost function is given as:

$$\Psi_{ij}(r_{ij}) = r_{ij} + r_{ij}(1 - \Psi_{ij}(t))$$

**Case 2:** In the pursuit of maximal total profit, the survival profit function is given as:

$$\Psi_{ij}(q_{ij}) = q_{ij} - q_{ij}(1 - \Psi_{ij}(t))$$

The addition of a survival cost/profit function to the conventional TP model may result in one of two possible outcomes.

**Case 1:** In the case of an objective function of the minimization type, the objective is to reduce the overall cost or damage while taking into account the probability of survival of the transported products.

**Model 2**

$$\text{Min } Z = \sum_{i=1}^I \sum_{j=1}^J \Psi_{ij}(r_{ij}) y_{ij}$$

Once the subsequent goal function has been simplified, the result is,

$$\text{Min } Z = 2 \sum_{i=1}^I \sum_{j=1}^J r_{ij} y_{ij} - \sum_{i=1}^I \sum_{j=1}^J r_{ij} \Psi_{ij}(t) y_{ij}$$

Subject to, Constraint (5)

**Case 2:** A maximization-type objective function aims to maximize overall profit while accounting for the probability of product survival.

**Model 3**

$$\text{Max } Z = \sum_{i=1}^I \sum_{j=1}^J \Psi_{ij}(q_{ij}) y_{ij}$$

After simplifying the goal function, we obtain

$$\text{Max } Z = \sum_{i=1}^I \sum_{j=1}^J q_{ij} \Psi_{ij}(t) y_{ij}$$

Subject to the constraint (5).

Models 2 and 3 represent the classical TPs with profit functions and survival costs, respectively.

Due to the implementation of various production planning strategies and prevailing market conditions, accurately quantifying the homogeneous product supply and demand in most TPs remains challenging. To ascertain the exact intervals within which the quantities will decrease, the DM must insert a change in the supply and demand quantities according to the circumstances.

Assumed to be variable in this instance, the quantity of supply  $s_i$  and demand  $d_j$  can be represented by  $\tilde{s}_i$  and  $\tilde{d}_j$ , respectively,

The following represents the mathematical models.

**Model 4**

$$\text{Min } Z = 2 \sum_{i=1}^I \sum_{j=1}^J r_{ij} y_{ij} - \sum_{i=1}^I \sum_{j=1}^J r_{ij} \Psi_{ij}(t) y_{ij}$$

Subject to:

$$\sum_{j=1}^J y_{ij} \leq \tilde{s}_i, \quad \forall i = 1, 2, \dots, I \tag{10}$$

$$\sum_{i=1}^I y_{ij} \geq \tilde{d}_j, \quad \forall j = 1, 2, \dots, J$$

$$y_{ij} \geq 0, \quad \forall i, j.$$

And the model 5 is given as,

$$\text{Max } Z = \sum_{i=1}^I \sum_{j=1}^J \Psi_{ij}(q_{ij}) y_{ij}$$

Subject to the constraint (7).

**8. Multi-objective transportation survival cost function with fuzzy parameters**

It is acknowledged that uncertainty, whether probabilistic or fuzzy, is essential to creating decision-making models. The decision maker’s inaccurate estimates are the source of the parameter ambiguity. In some situations, the problem’s solution should take this ambiguity into account. The goal function’s cost parameter is assumed to be fuzzy in this study. Fuzzy set theory-based ranking function techniques are used to convert this fuzziness into a clear or predictable result. The defuzzified discussion is described as follows:

The general mathematical model for the transportation survival cost function is given as:

$$\text{Min } Z = 2 \sum_{i=1}^I \sum_{j=1}^J r_{ij} y_{ij} - \sum_{i=1}^I \sum_{j=1}^J r_{ij} \Psi_{ij}(t) y_{ij}$$

Subject to the constraint (7).

The following formula (2) is used to de-fuzzify the cost parameter, which is a fuzzy number in the objective function of the problem:

**Model 6**

$$\text{Min } Z = 2 \sum_{i=1}^I \sum_{j=1}^J D(r_{ij}) y_{ij} - \sum_{i=1}^I \sum_{j=1}^J D(r_{ij}) \Psi_{ij}(t) y_{ij}$$

Subject to:

$$\sum_{j=1}^J y_{ij} \leq D(\tilde{s}_i), \quad i = 1, 2, \dots, I \tag{11}$$

$$\sum_{i=1}^I y_{ij} \geq D(\tilde{d}_j), \quad j = 1, 2, \dots, J$$

$$y_{ij} \geq 0, \quad \forall i, j.$$

where  $D(r_{ij})$  is the defuzzified value of  $(r_{ij})$

**9. Neutrosophic programming approach**

A new method for solving multi-objective TPs with fuzzy factors has been presented. This approach uses three membership functions: the minimum of the falsity membership function, the highest degree of truth, and the maximum indeterminacy. Let  $F$  stand for fuzzy judgments,  $G$  for fuzzy aims, and  $C$  for fuzzy constraints. The definition of the appropriate neutrosophic decision set, denoted by the notation  $F_N$ , is as follows:

$$F_n = \left( \bigcap_{p=1}^P G_p \right) \cap \left( \bigcap_{w=1}^W C_q \right) = (y, T_E(y), I_E(y), G_E(y)) \tag{12}$$

Where,

$$T_E(y) = \max \begin{bmatrix} T_{G_1}(y), T_{G_2}(y), T_{G_3}(y), \\ T_{C_1}(y), T_{C_1}(y) \end{bmatrix}, \quad \forall y \in Y \tag{13}$$

$$I_E(y) = \max \begin{bmatrix} I_{G_1}(y), I_{G_2}(y), I_{G_3}(y), \\ I_{C_1}(y), I_{C_1}(y) \end{bmatrix}, \quad \forall y \in Y \tag{14}$$

$$G_E(y) = \min \begin{bmatrix} G_{G_1}(y), G_{G_2}(y), G_{G_3}(y), \\ G_{C_1}(y), G_{C_1}(y) \end{bmatrix}, \quad \forall y \in Y \tag{15}$$

Regarding the decision set  $F_N$  of neutrosophic numbers, the truth, indeterminacy, and falsity degrees are provided by the functions  $T_F(y)$ ,  $I_F(y)$ ,  $G_F(y)$ . In order to determine the various membership functions for MOTPs, we have defined the limits for each objective function. The  $L_p$  and  $U_p$ , respectively, and can be obtained as follows: Initially, we addressed each objective function individually within the established limitations of the problem. Upon addressing p objectives independently, we obtain a collection of p solutions,  $Y^1, Y^2, \dots, Y^p$ . Subsequently, the derived solutions are substituted into each objective function to produce the lower and upper bounds for each objective, as outlined below:

$$U_p = \max [Z_p(Y^p)], \quad L_p = \min [Z_p(Y^p)], \quad p = 1, \dots, P \tag{16}$$

At this point, the upper and lower boundaries are, For truth membership:

$$U_p^T = U_p, \quad L_p^T = L_p \tag{17}$$

For indeterminacy membership:

$$U_p^I = L_p^T + s_p, \quad L_p^I = L_p^T \tag{18}$$

For falsity membership,

$$U_p^G = U_p^T, \quad L_p^G = L_p^T + t_k \tag{19}$$

The parameters  $s_k$  and  $t_k$  correspond to the lower and upper aspiration levels of each objective function. They are selected directly from the minimum and maximum values observed in the payoff matrix to ensure that the membership functions are aligned with realistic operational bounds. In this case, the DMs have predetermined real values  $s_k$  and  $t_k \in (0,1)$ . The linear membership functions are constructed using these lower and upper limits in a neutrosophic set as follows:

$$T_p(Z_p(y)) = \begin{cases} 1 & \text{if } Z_p(y) < L_p^T \\ \frac{U_p^T - Z_p(y)}{U_p^T - L_p^T} & \text{if } L_p^T \leq Z_p(y) \leq U_p^T \\ 0 & \text{if } Z_p(y) > U_p^T \end{cases} \tag{20}$$

$$I_p(Z_p(y)) = \begin{cases} 1 & \text{if } Z_p(y) < L_p^I \\ \frac{U_p^I - Z_p(y)}{U_p^I - L_p^I} & \text{if } L_p^I \leq Z_p(y) \leq U_p^I \\ 0 & \text{if } Z_p(y) > U_p^I \end{cases} \tag{21}$$

$$G_p(Z_p(y)) = \begin{cases} 1 & \text{if } Z_p(y) < L_p^G \\ \frac{U_p^G - Z_p(y)}{U_p^G - L_p^G} & \text{if } L_p^G \leq Z_p(y) \leq U_p^G \\ 0 & \text{if } Z_p(y) > U_p^G \end{cases} \tag{22}$$

The condition  $L_p^{(\cdot)} \neq U_p^{(\cdot)}$  holds for all objective functions. On the other hand, the equivalent membership function will be 1 if  $(L_p^{(\cdot)} = U_p^{(\cdot)})$

. The following formulation of the problem may be made using the methodology described in [Bellman and Zadeh \(1970\)](#):

$$\begin{aligned} & \max \min_{p=1,2,\dots,P} T_p(Z_p(y)) \\ & \max \min_{p=1,2,\dots,P} I_p(Z_p(y)) \\ & \min \max_{p=1,2,\dots,P} G_p(Z_p(y)) \\ & \sum_{j=1}^J y_{ij} \leq D(\tilde{s}_i), \quad i = 1, 2, \dots, I \tag{23} \end{aligned}$$

$$\begin{aligned} & \sum_{i=1}^I y_{ij} \geq D(\tilde{d}_j), \quad j = 1, 2, \dots, J \tag{24} \\ & y_{ij} \geq 0, \quad \forall i, j \end{aligned}$$

With the use of auxiliary parameters, the issue may be changed into the following form.

$$\max \delta \tag{25}$$

$$\max \beta \tag{26}$$

$$\min \Gamma \tag{27}$$

Subject to:

$$T_p(Z_p(\underline{y})) \geq \delta \tag{28}$$

$$I_p(Z_p(\underline{y})) \geq \beta \tag{29}$$

$$G_p(Z_p(\underline{y})) \leq \Gamma \tag{30}$$

$$\sum_{j=1}^J y_{ij} \leq D(\tilde{s}_i), \quad i=1,2,\dots,I \tag{31}$$

$$\sum_{i=1}^I y_{ij} \geq D(\tilde{d}_j), \quad j=1,2,\dots,J \tag{32}$$

$$y_{ij} \geq 0, \quad \forall i \text{ and } j$$

$$\alpha \geq \beta, \quad \alpha \geq \gamma, \quad \alpha + \beta + \gamma \leq 3, \quad \alpha, \beta, \gamma \in (0,1)$$

Using the above linear membership function, the problem can be written as,

$$\max \delta + \beta - \Gamma \tag{33}$$

Subject to,

$$\sum_{j=1}^J y_{ij} \leq D(s_i), \quad i=1,2,\dots,I \tag{34}$$

$$\sum_{i=1}^I y_{ij} \geq D(d_j), \quad j=1,2,\dots,J \tag{35}$$

$$y_{ij} \geq 0, \quad \forall i \text{ and } j$$

$$Z_p(\underline{y}) + (U_p^T - L_p^T)\alpha \leq U_p^T \tag{36}$$

$$Z_p(\underline{y}) + (U_p^I - L_p^I)\beta \leq U_p^I \tag{37}$$

$$Z_p(\underline{y}) + (U_p^G - L_p^G)\gamma \leq U_p^G \tag{38}$$

$$\alpha \geq 0, \quad \beta \geq 0, \quad \gamma \geq 0, \quad \alpha + \beta + \gamma \leq 3 \tag{39}$$

$$\alpha, \beta, \gamma \in (0,1) \tag{40}$$

Fig. 1 illustrates the 3D surface plot that represents the neutrosophic membership function space, showing how each decision alternative is evaluated across the truth (T), indeterminacy (I), and falsity (F) dimensions, capturing uncertainty, inconsistency, and hesitation in decision modeling.

### 10. NPA stepwise algorithms

The stages that make up the suggested method may be summed up as follows:

- As described in Section (7), formulate the MOTP using fuzzy parameters.
- To turn the problem into a crisp form, use the de-fuzzification method described in Equation (2).

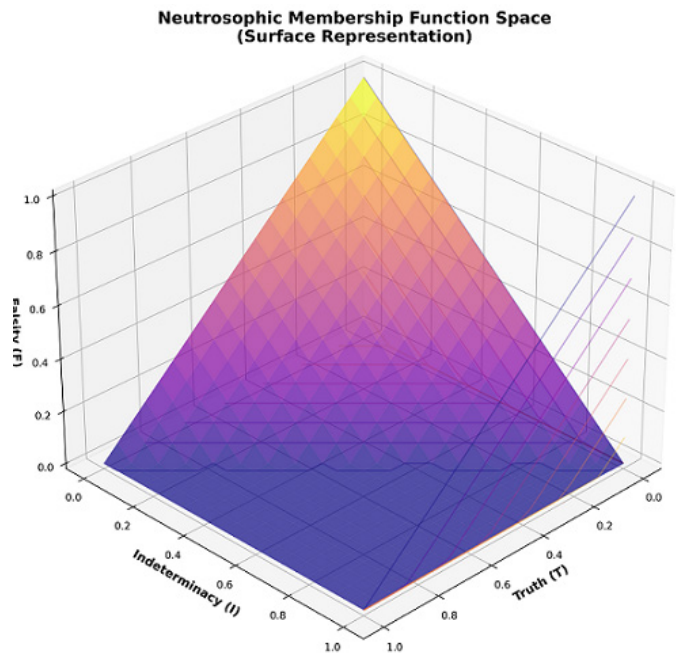


Fig. 1. Each decision alternative is evaluated across three independent membership dimensions representing truth, indeterminacy, and falsity in the neutrosophic environment.

- Determine the goal functions for the set of restrictions at each level to create a payoff matrix.
- Establish the upper and lower bounds for each stage's objective function.
- Determine the upper and lower bounds for the truth, indeterminacy, and falsity membership functions using Equations (16), (17), and (18).
- In a neutrosophic environment, define the linear membership function as shown by Equations (17) through (19).
- Equations (23) through (30) are used to create the neutrosophic problem, which is then transformed into a neutrosophic compromise programming problem using Equations (31) through (38).
- Utilizing the optimization software Lingo 16.0, find the compromise solution to the MOTP survival cost function.

### 11. Numerical problem

A pharmaceutical company is distributing its newly developed vaccine from four manufacturing plants in Maharashtra (India), located in Mumbai (S1), Pune (S2), Nagpur (S3), and Nashik (S4), to hospitals in four cities of Gujarat, namely Ahmedabad (D1), Surat (D2), Vadodara (D3), and Rajkot (D4). The DMs are unsure of the different transportation-related expenses because this is the first time the vaccine is being given in these areas. Naturally, because the distribution network is young, the exact amounts of supply and demand may not be known. The DMs thus use parabolic fuzzy numbers rather than fixed values to estimate all parameters because of the absence of accurate information. The transportation cost per unit and loss of time of the vaccine from different manufacturing plants to various hospital locations, denoted as  $(r_{ij}^{\Psi_{ij}})$ , has been presented in Table 1 along with fuzzy supply and demand constraints. Additionally, the labor and safety costs per unit incurred in transportation, represented as  $(r_{ij}^{\Psi_{ij}})$  and  $(r_{ij}^{\Psi_{ij}})$ , have been given in Tables 2 and 3, respectively. The company incurs a base cost for delivering the minimum required vaccine units to each hospital, and any excess supply beyond the agreed limit results in an additional charge per unit, in accordance with the company's regulations. The DMs of the pharmaceutical company aim to determine the optimal number of vaccine units to be transported from different plants to various hospitals while minimizing the costs of each objective under uncertain cost, supply, and demand conditions.

**Table 1.**

The cost of transportation per unit (in thousand) and loss of time ( $r_{ij}, \Psi_{ij}$ ) from sources to the destination.

	D <sub>1</sub>	D <sub>2</sub>	D <sub>3</sub>	D <sub>4</sub>	Supply
S <sub>1</sub>	(2.2,2.4,2.1;0.3)	(1.5,1.7,2.1;0.2)	(2.3,2.5,2.6;0.1)	(2.5,3.5,4.5;0.4)	(25,29,33)
S <sub>2</sub>	(1.2,2.2,3.2;0.4)	(1.4,1.8,2.2;0.2)	(2.8,3.7,4.8;0.3)	(0,2,4;0.1)	(16,26,36)
S <sub>3</sub>	(0,2,4;0.1)	(2,2.5,3.5;0.4)	(1.3,1.8,2.3;0.3)	(1.3,1.5,1.7;0.2)	(30,32,34)
S <sub>4</sub>	(2,2.3,2.6;0.3)	(2.5,2.9,3.3;0.4)	(2.2,2.8,3.4;0.1)	(2.2,2.4,2.6;0.2)	(24,28,32)
Demand	(20,22,24)	(20,22,24)	(25,29,33)	(30,34,38)	

**Table 2.**

Overall labor cost of unit product (in thousand) and loss of time ( $r_{ij}, \Psi_{ij}$ ) from sources to the destination.

	D <sub>1</sub>	D <sub>2</sub>	D <sub>3</sub>	D <sub>4</sub>	Supply
S <sub>1</sub>	(25,30,35;0.2)	(17,22,27;0.4)	(21,25,29;0.3)	(22,25,28;0.1)	(28,29,30)
S <sub>2</sub>	(15,20,25;0.2)	(20,25,30;0.4)	(14,18,22;0.2)	(20,24,28;0.2)	(21,26,31)
S <sub>3</sub>	(13,17,21;0.3)	(14,18,22;0.2)	(15,20,25;0.3)	(22,26,30;0.2)	(28,32,36)
S <sub>4</sub>	(24,28,32;0.3)	(23,26,29;0.3)	(22,25,28;0.15)	(24,26,28;0.25)	(25,28,31)
Demand	(18,22,26)	(19,22,25)	(19,29,39)	(28,34,40)	

**Table 3.**

Safety cost of unit product (in thousand) and loss of time ( $r_{ij}, \Psi_{ij}$ ) from sources to the destination.

	D <sub>1</sub>	D <sub>2</sub>	D <sub>3</sub>	D <sub>4</sub>	Supply
S <sub>1</sub>	(0.3,0.5,0.7;0.2)	(0.2,0.4,0.6;0.3)	(0.5,0.7,0.9;0.2)	(0.9,1.3,1.7;0.3)	(27,29,31)
S <sub>2</sub>	(0.4,0.8,1.2;0.4)	(0.5,0.9,1.3;0.2)	(0.5,0.6,0.7;0.3)	(1.2,1.5,1.8;0.1)	(22,26,30)
S <sub>3</sub>	(0.5,0.75,1;0.2)	(0.5,0.7,1;0.4)	(0.5,0.8,1;0.3)	(0.2,0.3,1;0.1)	(31,32,33)
S <sub>4</sub>	(0.8,0.9,1;0.4)	(0.3,0.7,1;0.2)	(0.5,0.6,0.9;0.3)	(0.4,0.8,1.2;0.1)	(26,28,30)
Demand	(17,22,27)	(21,22,23)	(28,29,30)	(29,34,39)	

In practical logistics settings, the survival cost reflects the risk of shipments failing to reach their destination within the acceptable time window, capturing delays, perishability, and reliability concerns. The labor and safety cost represents expenses related to workforce handling, accident prevention, and compliance with safety requirements, which are critical for operational sustainability. The time-loss cost measures delays and waiting times that increase operational inefficiency and reduce service quality. Together, these objectives capture the essential trade-offs faced by logistics managers in balancing reliability, safety, and timely delivery under uncertain conditions.

**Step 1.** The mathematical model of the above problem is formulated using the above information.

$$\begin{aligned} \min Z_1 = & 2((2.2,2.4,2.1)y_{11} + (1.5,1.7,2.1)y_{12} + (2.3,2.5,2.6)y_{13} \\ & + (2.5,3.5,4.5)y_{14} + (1.2,2.2,3.2)y_{21} + (1.4,1.8,2.2)y_{22} \\ & + (2.8,3.7,4.8)y_{23} + (0,2,4)y_{24} + (0,2,4)y_{31} + (2,2.5,3.5)y_{32} \\ & + (1.3,1.8,2.3)y_{33} + (1.3,1.5,1.7)y_{34} + (2,2.3,2.6)y_{41} \\ & + (2.5,2.9,3.3)y_{42} + (2.2,2.8,3.4)y_{43} + (2.2,2.4,2.6)y_{44}) \\ & - ((2.2,2.4,2.1;0.3)y_{11} + (1.5,1.7,2.1;0.2)y_{12} \\ & + (2.3,2.5,2.6;0.1)y_{13} + (2.5,3.5,4.5;0.4)y_{14} \\ & + (1.2,2.2,3.2;0.4)y_{21} + (1.4,1.8,2.2;0.2)y_{22} \\ & + (2.8,3.7,4.8;0.3)y_{23} + (0,2,4;0.1)y_{24} + (0,2,4;0.1)y_{31} \\ & + (2,2.5,3.5;0.4)y_{32} + (1.3,1.8,2.3;0.3)y_{33} \\ & + (1.3,1.5,1.7;0.2)y_{34} + (2,2.3,2.6;0.3)y_{41} \\ & + (2.5,2.9,3.3;0.4)y_{42} \\ & + (2.2,2.8,3.4;0.1)y_{43} + (2.2,2.4,2.6;0.2)y_{44}) \end{aligned}$$

$$\begin{aligned} \min Z_2 = & 2((25,30,35)y_{11} + (17,22,27)y_{12} + (21,25,29)y_{13} + (22,25,28)y_{14} \\ & + (15,20,25)y_{21} + (20,25,30)y_{22} + (14,18,22)y_{23} + (20,24,28)y_{24} \\ & + (13,17,21)y_{31} + (14,18,22)y_{32} + (15,20,25)y_{33} + (22,26,30)y_{34} \\ & + (24,28,32)y_{41} + (23,26,29)y_{42} + (22,25,28)y_{43} + (24,26,28)y_{44}) \\ & - ((25,30,35;0.2)y_{11} + (17,22,27;0.4)y_{12} + (21,25,29;0.3)y_{13} \\ & + (22,25,28;0.1)y_{14} + (15,20,25;0.2)y_{21} + (20,25,30;0.4)y_{22} \\ & + (14,18,22;0.2)y_{23} + (20,24,28;0.2)y_{24} + (13,17,21;0.3)y_{31} \\ & + (14,18,22;0.2)y_{32} + (15,20,25;0.3)y_{33} + (22,26,30;0.2)y_{34} \\ & + (24,28,32;0.3)y_{41} + (23,26,29;0.3)y_{42} + (22,25,28;0.15)y_{43} \\ & + (24,26,28;0.25)y_{44}) \end{aligned}$$

$$\begin{aligned} \min Z_3 = & 2((0.3,0.5,0.7)y_{11} + (0.2,0.4,0.6)y_{12} + (0.5,0.7,0.9)y_{13} \\ & + (0.9,1.3,1.7)y_{14} + (0.4,0.8,1.2)y_{21} + (0.5,0.9,1.3)y_{22} \\ & + (0.5,0.6,0.7)y_{23} + (1.2,1.5,1.8)y_{24} + (0.5,0.75,1)y_{31} \\ & + (0.5,0.7,1)y_{32} + (0.5,0.8,1)y_{33} + (0.2,0.3,1)y_{34} + (0.8,0.9,1)y_{41} \\ & + (0.3,0.7,1)y_{42} + (0.5,0.6,0.9)y_{43} + (0.4,0.8,1.2)y_{44}) \\ & - ((0.3,0.5,0.7;0.2)y_{11} + (0.2,0.4,0.6;0.3)y_{12} + (0.5,0.7,0.9;0.2)y_{13} \\ & + (0.9,1.3,1.7;0.3)y_{14} + (0.4,0.8,1.2;0.4)y_{21} + (0.5,0.9,1.3;0.2)y_{22} \\ & + (0.5,0.6,0.7;0.3)y_{23} + (1.2,1.5,1.8;0.1)y_{24} + (0.5,0.75,1;0.2)y_{31} \\ & + (0.5,0.7,1;0.4)y_{32} + (0.5,0.8,1;0.3)y_{33} + (0.2,0.3,1;0.1)y_{34} \\ & + (0.8,0.9,1;0.4)y_{41} + (0.3,0.7,1;0.2)y_{42} + (0.5,0.6,0.9;0.3)y_{43} \\ & + (0.4,0.8,1.2;0.1)y_{44}) \end{aligned}$$

**Step 2 :** The intermediate defuzzified cost, labor, and safety parameters obtained from the parabolic fuzzy numbers have been presented in Equation (2). These values serve as the crisp equivalents used to construct the payoff matrix

**Table 4.**  
Payoff Matrix of objective functions.

Decision variables	Z <sub>1</sub>	Z <sub>2</sub>	Z <sub>3</sub>
Y <sup>1</sup> (7,22,0,0,0,0,0,26,0,0,29,3,5,0,0,15)	372.32	4343.50	143.74
Y <sup>2</sup> (0,15,0,6,0,0,26,0,22,7,3,0,0,0,28)	489.80	3894	132.41
Y <sup>3</sup> (7,12,0,0,0,0,26,0,0,0,32,15,0,3,2)	431.83	4436.15	74.30

$$\begin{aligned} \min Z_1 = & 2(2.28y_{11} + 1.75y_{12} + 2.48y_{13} + 3.50y_{14} + 2.20y_{21} \\ & + 1.80y_{22} + 3.75y_{23} + 2.00y_{24} + 2.00y_{31} + 2.63y_{32} \\ & + 1.80y_{33} + 1.50y_{34} + 2.30y_{41} + 2.90y_{42} + 2.80y_{43} \\ & + 2.40y_{44}) - (0.684y_{11} + 0.35y_{12} + 0.248y_{13} + 1.40y_{14} \\ & + 0.88y_{21} + 0.36y_{22} + 1.125y_{23} + 0.20y_{24} + 0.20y_{31} \\ & + 1.052y_{32} + 0.54y_{33} + 0.30y_{34} + 0.69y_{41} + 1.16y_{42} \\ & + 0.28y_{43} + 0.48y_{44}) \end{aligned}$$

$$\begin{aligned} \min Z_2 = & 2(30y_{11} + 22y_{12} + 25y_{13} + 25y_{14} + 20y_{21} + 25y_{22} \\ & + 18y_{23} + 24y_{24} + 17y_{31} + 18y_{32} + 20y_{33} + 26y_{34} \\ & + 28y_{41} + 26y_{42} + 25y_{43} + 26y_{44}) - 6.0y_{11} + 8.8y_{12} \\ & + 7.5y_{13} + 2.5y_{14} + 4.0y_{21} + 10.0y_{22} + 3.6y_{23} + 4.8y_{24} \\ & + 5.1y_{31} + 3.6y_{32} + 6.0y_{33} + 5.2y_{34} + 8.4y_{41} + 7.8y_{42} \\ & + 3.75y_{43} + 6.5y_{44}) \end{aligned}$$

$$\begin{aligned} \min Z_3 = & 2(0.50y_{11} + 0.40y_{12} + 0.70y_{13} + 1.30y_{14} + 0.80y_{21} \\ & + 0.90y_{22} + 0.60y_{23} + 1.50y_{24} + 0.75y_{31} + 0.73y_{32} \\ & + 0.78y_{33} + 0.45y_{34} + 0.90y_{41} + 0.68y_{42} + 0.65y_{43} \\ & + 0.80y_{44}) - (0.10y_{11} + 0.12y_{12} + 0.14y_{13} + 0.39y_{14} \\ & + 0.18y_{22} + 0.18y_{23} + 0.15y_{24} + 0.15y_{31} + 0.292y_{32} \\ & + 0.234y_{33} + 0.045y_{34} + 0.36y_{41} + 0.136y_{42} + 0.195y_{43} \\ & + 0.08y_{44}) \end{aligned}$$

$$\begin{aligned} y_{11} + y_{12} + y_{13} + y_{14} & \leq 29 \\ y_{21} + y_{22} + y_{23} + y_{24} & \leq 26 \\ y_{31} + y_{32} + y_{33} + y_{34} & \leq 32 \\ y_{41} + y_{42} + y_{43} + y_{44} & \leq 28 \\ y_{11} + y_{21} + y_{31} + y_{41} & \geq 22 \\ y_{12} + y_{22} + y_{32} + y_{42} & \geq 22 \\ y_{13} + y_{23} + y_{33} + y_{43} & \geq 29 \\ y_{14} + y_{24} + y_{34} + y_{44} & \geq 34 \\ y_{ij} & \geq 0, \quad \forall i, j \in \{1, 2, 3, 4\} \end{aligned}$$

**Step 3:** Following the conclusion of each goal separately, the payoff matrix has been shown in Table 4

Table 4 presents a portion of the payoff matrix, which reports the objective values obtained by optimizing each goal independently. These values form the basis for determining the upper and lower bounds required for computing neutrosophic membership functions.

**Step 4:** We obtained the upper bound values:

$$U_1 = 489.80, \quad U_2 = 4436.15, \quad U_3 = 143.74$$

and the lower bound values:

$$L_1 = 372.32, \quad L_2 = 3894, \quad L_3 = 74.30$$

for each objective function.

**Steps 5 and 6:** We derive the truth, indeterminacy, and falsity membership function upper and lower limits. Next, we build the three objectives membership functions.

For Z<sub>1</sub>, the upper and lower bounds for the first objective and its membership function are:

$$U_1^T = U_1 = 489.80, \quad U_1^I = L_1^T + s_1 = 372.32 + s_1, \quad U_1^F = U_1^T = 489.80$$

$$L_1^T = L_1 = 372.32, \quad L_1^I = L_1^T = 372.32, \quad L_1^F = L_1^T + t_1 = 372.32 + t_1$$

$$T_1(Z_1(y)) = \begin{cases} 1 & \text{if } Z_1(y) < 372.32 \\ 1 - \frac{Z_1(y) - 372.32}{489.80 - 372.32} & \text{if } 372.30 \leq Z_1(y) \leq 489.80 \\ 0 & \text{if } Z_1(y) > 489.80 \end{cases}$$

$$I_1(Z_1(y)) = \begin{cases} 1 & \text{if } Z_1(y) < 372.32 \\ 1 - \frac{Z_1(y) - 372.32}{s_1} & \text{if } 372.30 \leq Z_1(y) \leq 372.32 + s_1 \\ 0 & \text{if } Z_1(y) > 372.32 + s_1 \end{cases}$$

$$G_1(Z_1(y)) = \begin{cases} 1 & \text{if } Z_1(y) < 489.80 \\ 1 - \frac{489.80 - Z_1(y)}{489.80 - 372.32 - t_1} & \text{if } 372.32 + t_1 \leq Z_1(y) \leq 489.80 \\ 0 & \text{if } Z_1(y) > 372.32 + t_1 \end{cases}$$

For Z<sub>2</sub>, the upper and lower bounds for the second objective and its membership functions are:

$$U_2^T = U_2 = 4436.15, \quad U_2^I = L_2^T + s_2 = 3894 + s_2, \quad U_2^F = U_2^T = 4436.15,$$

$$L_2^T = L_2 = 3894, \quad L_2^I = L_2^T = 3894, \quad L_2^F = L_2^T + t_2 = 3894 + t_2.$$

$$T_2(Z_2(y)) = \begin{cases} 1 & \text{if } Z_2(y) < 3894 \\ 1 - \frac{Z_2(y) - 3894}{4436.15 - 3894} & \text{if } 3894 \leq Z_2(y) \leq 4436.15 \\ 0 & \text{if } Z_2(y) > 4436.15 \end{cases}$$

$$I_2(Z_2(y)) = \begin{cases} 1 & \text{if } Z_2(y) < 3894 \\ 1 - \frac{Z_2(y) - 3894}{s_2} & \text{if } 3894 \leq Z_2(y) \leq 3894 + s_2 \\ 0 & \text{if } Z_2(y) > 3894 + s_2 \end{cases}$$

$$G_2(Z_2(y)) = \begin{cases} 1 & \text{if } Z_2(y) < 4436.15 \\ 1 - \frac{4436.15 - Z_2(y)}{4436.15 - 3894 - t_2} & \text{if } 3894 + t_2 \leq Z_2(y) \leq 4436.15 \\ 0 & \text{if } Z_2(y) > 3894 + t_2 \end{cases}$$

For Z<sub>3</sub>, the upper and lower bounds for the second objective and its membership functions are:

$$U_3^T = U_3 = 143.74, \quad U_3^I = L_3^T + s_3 = 74.30 + s_3, \quad U_3^F = U_3^T = 143.74,$$

$$L_3^T = L_3 = 74.30, \quad L_3^I = L_3^T = 74.30, \quad L_3^F = L_3^T + t_3 = 74.30 + t_3.$$

$$T_3(Z_3(\underline{y})) = \begin{cases} 1 & \text{if } Z_3(\underline{y}) < 74.30 \\ 1 - \frac{Z_3(\underline{y}) - 74.30}{143.74 - 74.30} & \text{if } 74.30 \leq Z_3(\underline{y}) \leq 143.74 \\ 0 & \text{if } Z_3(\underline{y}) > 143.74 \end{cases}$$

$$I_3(Z_3(\underline{y})) = \begin{cases} 1 & \text{if } Z_3(\underline{y}) < 74.30 \\ 1 - \frac{Z_3(\underline{y}) - 74.30}{s_3} & \text{if } 74.30 \leq Z_3(\underline{y}) \leq 74.30 + s_3 \\ 0 & \text{if } Z_3(\underline{y}) > 74.30 + s_3 \end{cases}$$

$$G_3(Z_3(\underline{y})) = \begin{cases} 1 & \text{if } Z_3(\underline{y}) < 143.74 \\ 1 - \frac{143.74 - Z_3(\underline{y})}{143.74 - 74.30 - t_3} & \text{if } 74.30 + t_3 \leq Z_3(\underline{y}) \leq 143.74 \\ 0 & \text{if } Z_3(\underline{y}) > 74.30 + t_3 \end{cases}$$

The following is the formulation of the Neutrosophic model for the multi-objective TP:

$$\max(\alpha + \beta - \gamma)$$

$$\begin{aligned} Y_{11} + Y_{12} + Y_{13} + Y_{14} &\leq 29, \\ Y_{21} + Y_{22} + Y_{23} + Y_{24} &\leq 26, \\ Y_{31} + Y_{32} + Y_{33} + Y_{34} &\leq 32, \\ Y_{41} + Y_{42} + Y_{43} + Y_{44} &\leq 28, \\ Y_{11} + Y_{21} + Y_{31} + Y_{41} &\geq 22, \\ Y_{12} + Y_{22} + Y_{32} + Y_{42} &\geq 22, \\ Y_{13} + Y_{23} + Y_{33} + Y_{43} &\geq 29, \\ Y_{14} + Y_{24} + Y_{34} + Y_{44} &\geq 34, \end{aligned}$$

$$Y_{ij} \geq 0, \quad \forall i, j \in \{1, 2, 3, 4\}.$$

$$2\{ 2.28y_{11} + 1.75y_{12} + 2.48y_{13} + 3.50y_{14} + 2.20y_{21} + 1.80y_{22} + 3.75y_{23} + 2.00y_{24} + 2.00y_{31} + 2.63y_{32} + 1.80y_{33} + 1.50y_{34} + 2.30y_{41} + 2.90y_{42} + 2.80y_{43} + 2.40y_{44} \} - \{0.684y_{11} + 0.35y_{12} + 0.248y_{13} + 1.40y_{14} + 0.88y_{21} + 0.36y_{22} + 1.125y_{23} + 0.20y_{24} + 0.20y_{31} + 1.052y_{32} + 0.54y_{33} + 0.30y_{34} + 0.69y_{41} + 1.16y_{42} + 0.28y_{43} + 0.48y_{44}\} + (489.80 - 372.32)\alpha \leq 489.80$$

$$2\{ 30y_{11} + 22y_{12} + 25y_{13} + 25y_{14} + 20y_{21} + 25y_{22} + 18y_{23} + 24y_{24} + 17y_{31} + 18y_{32} + 20y_{33} + 26y_{34} + 28y_{41} + 26y_{42} + 25y_{43} + 26y_{44} \} - \{6.0y_{11} + 8.8y_{12} + 7.5y_{13} + 2.5y_{14} + 4.0y_{21} + 10.0y_{22} + 3.6y_{23} + 4.8y_{24} + 5.1y_{31} + 3.6y_{32} + 6.0y_{33} + 5.2y_{34} + 8.4y_{41} + 7.8y_{42} + 3.75y_{43} + 6.5y_{44}\} + (4436.15 - 3894)\alpha \leq 4436.15$$

$$2\{ 0.50y_{11} + 0.40y_{12} + 0.70y_{13} + 1.30y_{14} + 0.80y_{21} + 0.90y_{22} + 0.60y_{23} + 1.50y_{24} + 0.75y_{31} + 0.73y_{32} + 0.78y_{33} + 0.45y_{34} + 0.90y_{41} + 0.68y_{42} + 0.65y_{43} + 0.80y_{44} \} - \{0.10y_{11} + 0.12y_{12} + 0.14y_{13} + 0.39y_{14} + 0.18y_{21} + 0.18y_{22} + 0.15y_{23} + 0.15y_{24} + 0.292y_{31} + 0.234y_{32} + 0.045y_{33} + 0.36y_{34} + 0.136y_{41} + 0.195y_{42} + 0.08y_{43} + 0.08y_{44}\} + (143.74 - 74.30)\alpha \leq 143.74$$

$$2\{ 2.28y_{11} + 1.75y_{12} + 2.48y_{13} + 3.50y_{14} + 2.20y_{21} + 1.80y_{22} + 3.75y_{23} + 2.00y_{24} + 2.00y_{31} + 2.63y_{32} + 1.80y_{33} + 1.50y_{34} + 2.30y_{41} + 2.90y_{42} + 2.80y_{43} + 2.40y_{44} \} - \{0.684y_{11} + 0.35y_{12} + 0.248y_{13} + 1.40y_{14} + 0.88y_{21} + 0.36y_{22} + 1.125y_{23} + 0.20y_{24} + 0.20y_{31} + 1.052y_{32} + 0.54y_{33} + 0.30y_{34} + 0.69y_{41} + 1.16y_{42} + 0.28y_{43} + 0.48y_{44}\} + s_1\beta \leq 372.32 + s_1$$

$$2\{ 30y_{11} + 22y_{12} + 25y_{13} + 25y_{14} + 20y_{21} + 25y_{22} + 18y_{23} + 24y_{24} + 17y_{31} + 18y_{32} + 20y_{33} + 26y_{34} + 28y_{41} + 26y_{42} + 25y_{43} + 26y_{44} \} - \{6.0y_{11} + 8.8y_{12} + 7.5y_{13} + 2.5y_{14} + 4.0y_{21} + 10.0y_{22} + 3.6y_{23} + 4.8y_{24} + 5.1y_{31} + 3.6y_{32} + 6.0y_{33} + 5.2y_{34} + 8.4y_{41} + 7.8y_{42} + 3.75y_{43} + 6.5y_{44}\} + s_2\beta \leq 3894 + s_2$$

$$2\{ 0.50y_{11} + 0.40y_{12} + 0.70y_{13} + 1.30y_{14} + 0.80y_{21} + 0.90y_{22} + 0.60y_{23} + 1.50y_{24} + 0.75y_{31} + 0.73y_{32} + 0.78y_{33} + 0.45y_{34} + 0.90y_{41} + 0.68y_{42} + 0.65y_{43} + 0.80y_{44} \} - \{0.10y_{11} + 0.12y_{12} + 0.14y_{13} + 0.39y_{14} + 0.18y_{21} + 0.18y_{22} + 0.15y_{23} + 0.15y_{24} + 0.292y_{31} + 0.234y_{32} + 0.045y_{33} + 0.36y_{34} + 0.136y_{41} + 0.195y_{42} + 0.08y_{43} + 0.08y_{44}\} + s_3\beta \leq 74.30 + s_3$$

$$2\{ 2.28y_{11} + 1.75y_{12} + 2.48y_{13} + 3.50y_{14} + 2.20y_{21} + 1.80y_{22} + 3.75y_{23} + 2.00y_{24} + 2.00y_{31} + 2.63y_{32} + 1.80y_{33} + 1.50y_{34} + 2.30y_{41} + 2.90y_{42} + 2.80y_{43} + 2.40y_{44} \} - \{0.684y_{11} + 0.35y_{12} + 0.248y_{13} + 1.40y_{14} + 0.88y_{21} + 0.36y_{22} + 1.125y_{23} + 0.20y_{24} + 0.20y_{31} + 1.052y_{32} + 0.54y_{33} + 0.30y_{34} + 0.69y_{41} + 1.16y_{42} + 0.28y_{43} + 0.48y_{44}\} - (489.80 - 372.32 + t_1)\gamma \leq 372.32 + t_1$$

**Table 5.**  
Optimal values for decision variables.

$y_{11}$	$y_{21}$	$y_{31}$	$y_{41}$	$y_{12}$	$y_{22}$	$y_{32}$	$y_{42}$	$y_{13}$	$y_{23}$	$y_{33}$	$y_{43}$	$y_{14}$	$y_{24}$	$y_{34}$	$y_{44}$
0	22	8	0	13	0	15	0	6	0	3	25	3	0	0	7

**Table 6.**  
Optimal values for the objective function.

$Z_1$	$Z_2$	$Z_3$
390.30	3978.21	84.72

$$2\{ 30y_{11} + 22y_{12} + 25y_{13} + 25y_{14} + 20y_{21} + 25y_{22} + 18y_{23} + 24y_{24} + 17y_{31} + 18y_{32} + 20y_{33} + 26y_{34} + 28y_{41} + 26y_{42} + 25y_{43} + 26y_{44} \} - \{ 6.0y_{11} + 8.8y_{12} + 7.5y_{13} + 2.5y_{14} + 4.0y_{21} + 10.0y_{22} + 3.6y_{23} + 4.8y_{24} + 5.1y_{31} + 3.6y_{32} + 6.0y_{33} + 5.2y_{34} + 8.4y_{41} + 7.8y_{42} + 3.75y_{43} + 6.5y_{44} \} - (4436.15 - 3894 + t_2)\gamma \leq 3894 + t_2$$

$$2\{ 0.50y_{11} + 0.40y_{12} + 0.70y_{13} + 1.30y_{14} + 0.80y_{21} + 0.90y_{22} + 0.60y_{23} + 1.50y_{24} + 0.75y_{31} + 0.73y_{32} + 0.78y_{33} + 0.45y_{34} + 0.90y_{41} + 0.68y_{42} + 0.65y_{43} + 0.80y_{44} \} - \{ 0.10y_{11} + 0.12y_{12} + 0.14y_{13} + 0.39y_{14} + 0.18y_{21} + 0.18y_{22} + 0.15y_{23} + 0.15y_{24} + 0.292y_{31} + 0.234y_{32} + 0.045y_{33} + 0.36y_{34} + 0.136y_{41} + 0.195y_{42} + 0.08y_{43} + 0.08y_{44} \} - (143.74 - 74.30 + t_3)\gamma \leq 74.30 + t_3$$

$$\alpha \geq \beta, \quad \alpha \geq \gamma, \quad \alpha + \beta + \gamma \leq 3\alpha$$

$$\beta, \gamma \in (0,1)$$

$$0 \leq s_k, t_k \leq 1, \quad \forall k = 1,2,3$$

The optimization software Lingo 16.0 was used to solve this MOTP model with neutrosophic parameters. Table 5 displays this model's optimum solution.

Tables 5 and 6 represent the values of decision variables and objective functions. Where  $Z_1$  is the cost of transportation, which is 390.30, and  $Z_2$  represent the overall labor cost, which is 3978.21, and  $Z_3$  is the safety cost of the unit product, which is 84.72.

Figs. 2 and 3 are the graphical representations of the decision variables and the objective functions.

### 12. Sensitivity analysis and model validation

To evaluate the robustness and applicability of the proposed neutrosophic fuzzy programming model, a sensitivity analysis was conducted on the neutrosophic parameters. Specifically, the degrees of truth (T), indeterminacy (I), and falsity (F) were independently varied by  $\pm 10\%$  and  $\pm 20\%$ , and the resulting changes in the three objective functions ( $Z_1, Z_2, Z_3$ ) were recorded.

The stability and practical applicability of the model are confirmed by the findings, which show that small variations in neutrosophic parameters result in very modest fluctuations in objective values. As a result, the suggested approach works well in practical settings where a precise parameter estimate is difficult. For every scenario, the model was re-solved, and we reported the absolute objective values for  $Z_1, Z_2$ , and  $Z_3$ . The absolute deviation from the baseline and the percentage deviation. Table 7 shows the variation in the objective functions after varying the parameter, and also shows the improvements and reductions in the values of the objective functions.

Table 7 shows that the proposed neutrosophic programming model remains stable under different perturbations of T, I, and F. A +10% increase in truth membership yields small improvements across all objectives, confirming that higher certainty supports better performance. Reducing truth by 10% leads to slight decreases, but the deviations

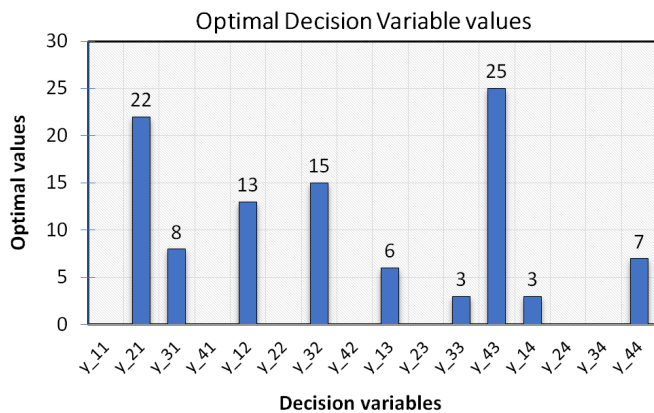


Fig. 2. Optimal decision variable values.

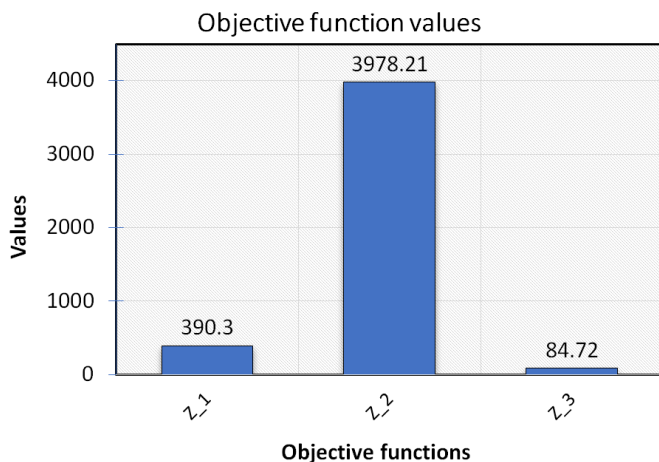


Fig. 3. Values of objective functions.

**Table 7.**  
Sensitivity analysis of neutrosophic parameters.

Variation in parameter	$\Delta Z_1$ (%)	$\Delta Z_2$ (%)	$\Delta Z_3$ (%)	Observation
+10% in truth	+2.3	+1.8	+0.9	Stable improvement in objectives
-10% in truth	-2.1	-1.5	-0.7	Slight reduction; model stable
+10% in indeterminacy	+0.5	+0.4	+0.2	Minimal effect (robust)
+20% in falsity	-3.8	-4.1	-2.2	Moderate decline; within tolerance

**Table 8.** Comparative Study between fuzzy, intuitionistic, and neutrosophic programming.

Decision variables and objective functions	FPA	IFA	NPA
$y_{11}$	16	0	0
$y_{21}$	0	15	22
$y_{31}$	0	1	8
$y_{41}$	0	0	0
$y_{12}$	25	27	13
$y_{22}$	0	0	0
$y_{32}$	0	0	15
$y_{42}$	0	2	0
$y_{13}$	30	0	6
$y_{23}$	0	0	0
$y_{33}$	0	0	3
$y_{43}$	5	16	25
$y_{14}$	38	0	3
$y_{24}$	0	0	0
$y_{34}$	28	0	0
$y_{44}$	0	30	7
Min $Z_1$	431.83	425.63	390.30
Min $Z_2$	4436.15	4236.15	3978.21
Min $Z_3$	141.00	128.72	84.72

remain modest. Variations in indeterminacy produce minimal impact, indicating strong robustness to hesitation or incomplete information. Even a +20% increase in falsity causes only moderate declines, all of which fall within operational tolerance. Overall, the model demonstrates practical robustness and maintains consistent objective behavior under realistic uncertainty levels.

**13. Managerial and operational implications**

The integration of survival cost functions within the neutrosophic programming framework has a significant impact on logistics and transportation planning. The survival cost denotes the probability-adjusted expense of timely goods delivery, enabling DMs to consider delivery delays, product decay, and related penalties.

The suggested model provides transportation managers with a decision-support tool that addresses several conflicting objectives, including transportation costs, labor expenses, and safety risks, while also considering uncertainty. By formally modeling indeterminacy, planners can create more robust supply chains that can adjust to variable situations. Logistics businesses can ascertain routes or suppliers with the highest likelihood of success while adhering to acceptable cost parameters. From an operational perspective, the model can inform resource allocation, risk reduction, and contingency planning in extensive distribution systems. However, certain limits are present. The approach presumes static parameter distributions and entails significant computing complexity when applied to extensive networks. Future research may integrate hybrid heuristics, dynamic demand updates, or alternative neutrosophic hybrid models to improve scalability and efficiency.

The above analyses reinforce that the proposed neutrosophic fuzzy programming approach (FPA) not only provides accurate quantitative outcomes but also offers strategic insight into managing uncertainty in multiobjective transportation systems.

The suggested model improves decision-making from a managerial perspective by clearly balancing risk, dependability, and cost effectiveness. The neutrosophic membership structure allows managers to simulate uncertainty and contradicting information, and the addition

of survival cost helps them to account for the likelihood of delay-related losses. In real-world logistics systems, this results in more robust routing plans, better resource allocation, and increased readiness for unpredictable events.

**14. Comparative study**

Considering fairness and consistency, the same dataset, constraints, and objective functions were used to solve the fuzzy, intuitionistic, and neutrosophic models. Table 8 presents a comparative analysis of the optimal solutions obtained using FPA, Intuitionistic Fuzzy Approach (IFA), and Neutrosophic Programming Approach (NPA) for the MOTP. The table reports the decision variables  $y_{ij}$  and the corresponding objective values  $Z_1, Z_2$  and  $Z_3$  for each approach. The FPA yields a feasible solution with higher overall costs. The total minimum transportation cost  $Z_1$  for FPA is 431.83, total labor cost  $Z_2$  is 4436.15, and the safety cost  $Z_3$  is 141. In IFA, the corresponding objective values decrease to 425.63, 4236.15, and 128.72, respectively. The NPA demonstrates superior performance across all objectives. By introducing the truth, indeterminacy, and falsity membership functions, it captures the uncertainty, hesitation, and inconsistency inherent in real-world transportation data. Consequently, the minimum objective values obtained are 390.30 for  $Z_1$ , 3978.21 for  $Z_2$  and 84.72 for  $Z_3$ . These results clearly show that the neutrosophic programming model produces more optimal, stable, and balanced solutions compared with fuzzy and intuitionistic approaches. It effectively minimizes total cost, labor, and safety risks by incorporating higher-order uncertainty through the neutrosophic logic framework. This improvement can be attributed to the survival-cost-based modelling and the extra flexibility provided by the Truth, Indeterminacy, and Falsity structure, which allows for more dependable and complete judgments in the face of uncertainty.

**15. Managerial insights**

For logistics managers, the outcomes of the suggested neutrosophic programming model offer several useful implications. First, by taking survival cost into consideration, managers may more accurately design routes and allocate resources by taking reliability problems and delay-related hazards into account. Second, by identifying vagueness, hesitancy, and conflicting information in transportation data, the hybrid parabolic fuzzy–neutrosophic structure facilitates balanced decision-making under uncertainty. Third, the comparison findings demonstrate that the neutrosophic method helps managers minimize operational risks and unanticipated costs by offering more consistent and lower objective values than fuzzy and intuitionistic benchmarks. All things considered, the framework provides a straightforward and trustworthy instrument for enhancing logistics performance in complex and unpredictable settings.

**16. Conclusions**

MOTPs are one of the most critical components of the manufacturing firm’s profit outcomes. If variability in transportation is not well handled, it may cause many inconveniences, and it has an added downside of losing sales and customer loyalty. This research resolves the vagueness associated with a MOTP concerning fuzzy parameters and time-dependent variables. The study then defines NPA as an enhanced method for identifying the compromise solution.

The primary contributions of this research are as follows:

- The architectural model presented in this paper combines fuzzy variables and time-dependent variables, making it more useful for solving practical problems in the real world.
- The study focuses on the rather limited area of indeterminacy and brings fresh and considerable input.
- In fact, applying the proposed approach allows considering it rather flexible and fitting for different domains such as supplier selection, advertising strategies, or portfolio optimization.

In this research, the time-dependent variable is included in the MOTP with fuzzy parameters. It also indicates that intuitionistic parameters can replace fuzzy parameters. Further research could examine the use of this method with other probabilities besides normal distribution and other types of fuzzy numbers, intuitionistic fuzzy sets.

#### CRedit authorship contribution statement

**Nabil Ahmed Khan:** Investigation, methodology, modeling, software, writing – original draft; **Sadiq Ali:** Formal analysis, funding acquisition, resources, validation, writing – review & editing; **SK Safdar Hossain:** Data curation, formal analysis, resources; **Ahmad Yusuf Adhami:** Conceptualization, investigation, modeling, writing – original draft; writing – review & editing.

#### Declaration of competing interest

The authors declare that they have no competing financial interests or personal relationships that could have influenced the work presented in this paper.

#### Data availability

Data are contained within the article.

#### Declaration of generative AI and AI-assisted technologies in the writing process

The authors confirm that there was no use of artificial intelligence (AI)-assisted technology for assisting in the writing or editing of the manuscript and no images were manipulated using AI.

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