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Supplier Selection Problem with Type-2 Fuzzy Parameters: A Neutrosophic Optimization Approach

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Abstract This paper investigates the multiobjective supplier selection problem (SSP) with type-2 fuzzy parameters. All the involved parameters such as aggregate demand, budget allocation, quota flexibility, rating values, are depicted as type-2 triangular fuzzy (T-2TF) parameters. To tackle the T-2TF, first, critical values (CV)-based reduction method is introduced, and then chance-constrained programming is modeled to obtain the crisp version of the multiobjective SSP. Secondly, an interval-based approximation method is also developed for defuzzifying the T-2TF parameters. Further, a novel interactive neutrosophic programming approach is also suggested to solve the deterministic multiobjective SSP, which allows the decision-makers to incorporate the neutral thoughts or indeterminacy degrees efficiently. The computational study is presented to verify and validate the defuzzfied techniques and the proposed solution approach. An ample opportunity to select the most desired compromise solution with maximum overall satisfaction level is also addressed. Finally, the conclusions and future research direction are revealed based on the discussed work.

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1 Introduction

The existence of uncertainty is trivial in real-life problems. Many decision-making scenarios inevitably yield an uncertain environment while modeling optimization problems. The incomplete, inconsistent, and inappropriate information about the system leads to uncertainty. Vagueness and ambiguousness among the different parameters' values are represented using the fuzzy set (FS) theory. Firstly, Zadeh [37] investigated the FS that tackles the membership function of an element into the feasible decision set. For complex data, the depiction of vagueness or ambiguity through a single membership function are not equally feasible. The abrupt fluctuation among the values of imprecise parameters occurs according to the changes in the decision-making environment. Due to the complexity of real-life problems, it may not be feasible to depict the fuzzy parameters with a single membership function. However, a set of corresponding membership grades can be a better representative of the degree of belongingness in a more appropriate way. Thus, the extension of FS with a set membership degree is introduced by Zadeh [38] and named as the type-2 fuzzy set (T-2FS). The T-2FS allows the decision-maker to convey the parameters with a set of membership grades into the FS (or type-1 fuzzy set). Therefore, the concept of type-1 and type-2 membership functions came into existence. For each type-1 membership function (or only membership function), there is a type-2 membership function associated with it and ensures the wholesome alignment of uncertainty degrees in the T-2FS.

In the area of T-2FS, many researchers have made a significant contribution to both the theoretical and application-level domain. Liang and Mendel [17] performed a theoretical study on type-2 fuzzy parameters. Mendel and John [21] also examined the necessary operations on type-2 fuzzy sets. Uncu and Turksen [32] discussed the discrete interval type-2 fuzzy models in learning parameters using uncertainty. Wu and Mendel [33] also investigated the uncertainty measures in interval type-2 fuzzy parameters. Juang and Tsao [12] discussed the interval type-2 fuzzy neural network for online learning. Nie and Tan [24] contributed to the reduction method of type-2 fuzzy parameters. Lam and Seneviratne [16] performed a stability analysis of the interval type-2 fuzzy model under the control system. Kundu et al. [13–15] have also attempted to solve the different sorts of transportation problems under interval type-2 fuzzy parameters. Muhuri et al. [23] studied a reliability redundancy problem under type-2 fuzzy uncertainty. Olivas et al. [25] presented an ant bee colony optimization technique with type-2 fuzzy uncertainty. Qin et al. [26] generalized the multicriteria group decision-making problem for the green supplier selection with interval type-2 fuzzy parameters. Liu et al. [20] also addressed a novel green supplier selection technique by combining quality function deployment.

The supplier selection problem is a well-known and integral component of the supply chain planning problems. The selection of best suppliers depends on various criteria such as overall performance ratings, less rejection of items, timely delivery, fulfilling aggregate demand. The literature suggested that a large part is dedicated to SSP as a multicriteria decision-making problem in interval type-2 fuzzy uncertainty. Türk et al. [31] investigated the application of interval type-2 fuzzy parameters in supplier selection problems. Sang and Liu [27] presented an interval type-2 fuzzy multicriteria decision-making problem with an application in supplier selection problems. Ghorabaee et al. [10] studied a green supplier selection by considering interval type-2 fuzzy parameters in multicriteria decision-making. Heidarzade et al. [11] also presented the supplier selection technique using the clustering method with interval type-2 fuzzy parameters. Mousakhani et al. [22] also implemented type-2 fuzzy parameters in the green supplier selection problem. Liu et al. [19] developed an integrated supplier selection model under the type-2 fuzzy parameters. Recently, Wu et al. [34] investigated an extended green supplier selection problem with type-2 fuzzy uncertainty.

A neutrosophic set (NS) is the extension and generalization of FS and intuitionistic fuzzy set (IFS), which is presented by Smarandache [29]. It manages the indeterminacy degrees or neutral thoughts while making decisions. Thus the marginal evaluations of each objective function are determined by truth, indeterminacy, and falsity degrees under the neutrosophic decision set. Based on NS, Ahmad and Adhami [3, 4], Ahmad et al. [5, 7] addressed neutrosophic programming approach for solving the multiobjective optimization problems. Many researchers such as Abdel-Basset et al. [1], Adhami and Ahmad [2], Ye [36] also contributed in the neutrosophic research domain. Here, we have developed an interactive neutrosophic programming approach (INPA) to solve the multiobjective SSP with type-2 fuzzy parameters. The proposed INPA can be considered as the extension of Ahmad et al. [6, 7], Torabi and Hassini [30], respectively. We have discussed the multiobjective SSP while ensuring the flow of the ordered quantity of items to different suppliers with type-2 fuzzy parameters. A novel solution approach is suggested for solving multiobjective SSP based on the neutrosophic set.

Various decision-making problems inherently contain vagueness or ambiguousness in the data-set. This incomplete information is conveyed either in the form of approximate intervals or linguistic terms. In SSP, the system parameters' available data/possible values cannot always be precisely determined and known. For instance, the price of a unit item at a supplier is "about 510$", say between 450$ and 560$, the available supply quantity of a supplier is "around 350–380 units", etc. Thus due to irregularities and inconsistencies like lack of input information, inappropriate and incomplete knowledge, noise in data, flawed statistical analysis, etc., it is sometimes hard to identify exact membership grades and, hence, model the problems in terms of type-1 fuzzy sets. As a result, T2-FS has emerged due to fuzziness in the membership function. Usually, the experts' possible values of parameters in approximate intervals, linguistic terms, etc. Also, each of the points in a given interval may not have the same importance or possibility. For a large data-set of a specific parameter collected from previous experiments, generally, all the points are not equally possible. Such types of linguistic information, approximate intervals, and blurred data-set can be expressed by T2-FSs, where the membership degree of each point cannot be precisely determined. The three-dimensional nature of a T2-FS gives an extra degree of freedom to represent uncertainty over the type-1 fuzzy set.

For the multiobjective SSP with fuzzy information, we have two motivations to explore this problem within the type-2 fuzzy set theory framework. Firstly, it is more advanced and typical to treat some critical parameters as type-2 fuzzy variables because of the practical difficulties in determining their crisp membership functions. Secondly, when some parameters are assumed to be T2-FS, designing an effective method to handle the optimization problem is also challenging.

The main contribution to this research can be regarded as follows:

- Most of the supplier selection problems are studied as multicriteria decision-making problems under T2-FSs, but here, we have presented multiobjective SSP with continuous type-2 fuzzy parameters at different degrees of vagueness.

- The continuous type-2 fuzzy parameters are dealt with two different techniques, such as critical values reduction and nearest interval approximation methods for obtaining the corresponding crisp version.
- An interactive neutrosophic programming approach (INPA) is proposed to solve the crisp multiobjective SSP, which considered the degree of indeterminacy while making decisions.
- Opportunity for generating the desired solution results by tuning the degree of vagueness (α) and compensation co-efficient (η) is also suggested.

The remaining portion of the manuscript is presented as follows: In Sect. 2, the concept of type-2 fuzzy set is discussed while Sect. 3 represents the formulation of multi-objective SSP under type-2 fuzzy parameters. The proposed INPA is presented in Sect. 4. In Sect. 5, a computational study is addressed to verify the applicability and validity of the proposed solution approach. The conclusions and future research opportunities are discussed in Sect. 6.

2 Preliminaries

In this section, we have discussed some basic concepts related to Type-2 fuzzy set.

Definition 1 [37] (*Fuzzy set or type-1 fuzzy set*) Suppose a universal set X, then a fuzzy set (FS) $\widetilde{A}$ in X can be defined as follows:

$$\widetilde{A} = \{x,\ \mu_{\widetilde{A}}(x) \,|\, x \in X\}$$

where $\mu_{\widetilde{A}}(x) : x \to [0,\ 1]$ denotes the membership function of the element x into the set $\widetilde{A}$, with the condition $0 \leq \mu_{\widetilde{A}}(x) \leq 1$.

Definition 2 [21] (*Type-2 fuzzy set*) An FS is said to be Type-2 fuzzy set (T-2FS) if the membership function (degree of belongingness) is also fuzzy, it means that the membership function for each element into the set is not a crisp value but represented by a fuzzy set. Such a membership degree is known as the type-2 membership function. Thus, a T-2FS $\widetilde{A}$ can be stated as follows:

$$\widetilde{A} = \left\{ \left((x, w)\ \mu_{\widetilde{A}}(x, w) \right) \,|\, x \in X,\ w \in V_x \subseteq [0,\ 1] \right\}$$

where $\mu_{\widetilde{A}}(x, w) : (x, w) \to [0,\ 1]$ denotes the type-2 membership function, V_x is the type-1 membership function of $x \in X$ which is the domain of type-2 membership function $\mu_{\widetilde{A}}(x)$ into the set $\widetilde{A}$ and can be defined as follows:

$$\widetilde{A} = \int_{x \in X} \int_{w \in V_x} \mu_{\widetilde{A}}(x, w)/(x, w),\ \ w \in V_x \subseteq [0,\ 1]$$

where $\int \int$ represent the union over entire permissible x and w. For discrete universal discourse, $\int$ is interchanged by $\sum$.

For each x, assume $x = x'$, the type-2 membership function [21], represented by $\mu_{\widetilde{A}}(x = x', w),\ w \in V_x \subseteq [0,\ 1]$ can be depicted as follows:

$$\mu_{\widetilde{A}}(x', w) = \mu_{\widetilde{A}}(x') = \int_{w \in V_{x'}} f_{x'}(w)/w,$$

where $0 \leq f_{x'}(w) \leq 1$. In particular, $w = w' \in V_{x'}, f_{x'}(w') = \mu_{\widetilde{A}}(x', w')$ is known as type-2 membership function. Therefore, $\widetilde{A}$ can be represented as follows:

$$\widetilde{A} = \{x,\ \widetilde{\mu}_{\widetilde{A}}(x) \,|\, x \in X\}$$

or

$$\widetilde{A} = \int_{x \in X} \widetilde{\mu}_{\widetilde{A}}(x)/x = \int_{x \in X} \left[\int_{w \in V_x} f_x(w)/w \right] /x$$

If all the type-2 membership functions are 1 (e.g., $f_x(w) = 1,\ \forall x, w$), the T-2FS is reduced into interval type-2 fuzzy set (IT-2FS) [21]. The characterization of an IT-2FS using footprint of uncertainty (FOU) depicts a two-dimensional plane containing points x and their type-1 membership functions V_x. More precisely, FOU admit the uncertainty in the type-1 membership functions of an IT-2FS.

Example 1 Suppose $X = \{4, 5, 6\}$ and the type-1 membership functions of the elements of X are $V_4 = \{0.3, 0.4, 0.6\}$, $V_5 = \{0.6, 0.8, 0.9\}$ and $V_6 = \{0.5, 0.6, 0.7, 0.8\}$ respectively. Now, one can obtained the type-2 membership function of the element 4 as follows:

$$\begin{aligned}\widetilde{\mu}_{\widetilde{A}}(4) &= \mu_{\widetilde{A}}(4, w) \\ &= (0.6/0.3) + (1.0/0.4) + (0.7/0.6) \\ &\approx \begin{pmatrix} 0.3,\ 0.4,\ 0.6 \\ 0.6,\ 1.0,\ 0.7 \end{pmatrix}\end{aligned}$$

More specifically, $\mu_{\widetilde{A}}(4, 0.3) = 0.6$, $\mu_{\widetilde{A}}(4, 0.4) = 1.0$ and $\mu_{\widetilde{A}}(4, 0.6) = 0.7$. Furthermore $\mu_{\widetilde{A}}(4, 0.3) = 0.6$ means membership function (type-2) of the element 4 having the membership grade (type-1) 0.3 is 0.6. Thus $\widetilde{A}$ comply on the value 4 with membership $\begin{pmatrix} 0.3,\ 0.4,\ 0.6 \\ 0.6,\ 1.0,\ 0.7 \end{pmatrix}$, which depicts a random fuzzy variable.

Similarly,

$$\widetilde{\mu}_{\widetilde{A}}(5) = \mu_{\widetilde{A}}(5, w) = (0.7/0.6) + (1.0/0.8) + (0.8/0.9),$$

$$\widetilde{\mu}_{\widetilde{A}}(6) = \mu_{\widetilde{A}}(6, w) = (0.3/0.5) + (0.4/0.6) + (1.0/0.7) + (0.5/0.8)$$

Hence, the discrete type-2 fuzzy variable $\widetilde{A}$ can be presented as follows:

$$\widetilde{A} = (0.6/0.3)/4 + (1.0/0.4)/4 + (0.7/0.6)/4 + (0.7/0.6)/5 + (1.0/0.8)/5 + (0.8/0.9)/5 + (0.3/0.5)/6 + (0.4/0.6)/6 + (1.0/0.7)/6 + (0.5/0.8)/6,$$

Definition 3 [21] (*Type-2 triangular fuzzy variable*) A type-2 triangular fuzzy variable $\widetilde{\psi}$ is depicted by $(s_1, s_2, s_3; \eta_l, \eta_r)$, where s_1, s_2, s_3 are the real numbers and $\eta_l, \eta_r \in [0, 1]$ are the two parameters identifying the degree of vagueness or ambiguity that $\widetilde{\psi}$ takes a value x and the secondary possibility distribution function $\widetilde{\mu}_{\widetilde{\psi}}(x)$ of $\widetilde{\psi}$ is depicted by

$$\widetilde{\mu}_{\widetilde{\psi}}(x) = \left[\frac{x - s_1}{s_2 - s_1} - \eta_l \min\left(\frac{x - s_1}{s_2 - s_1}, \frac{s_2 - x}{s_2 - s_1}\right), \frac{x - s_1}{s_2 - s_1}, \frac{x - s_1}{s_2 - s_1} + \eta_r \min\left(\frac{x - s_1}{s_2 - s_1}, \frac{s_2 - x}{s_2 - s_1}\right)\right] \quad (1)$$

for any $x \in (s_1, s_2)$, and

$$\widetilde{\mu}_{\widetilde{\psi}}(x) = \left[\frac{s_3 - x}{s_3 - s_2} - \eta_l \min\left(\frac{s_3 - x}{s_3 - s_2}, \frac{x - s_2}{s_3 - s_2}\right), \frac{s_3 - x}{s_3 - s_2}, \frac{s_3 - x}{s_3 - s_2} + \eta_r \min\left(\frac{s_3 - x}{s_3 - s_2}, \frac{x - s_2}{s_3 - s_2}\right)\right] \quad (2)$$

A type-2 triangular fuzzy variable (T-2TFV) can be considered as the generalization of a triangular fuzzy variable (TFV). In TFV (s_1, s_2, s_3), the degree of belongingness (membership function) of each element is a fixed point in [0, 1]. Moreover, the type-1 membership function in a T-2TFV $\widetilde{\psi} = (s_1, s_2, s_3; \eta_l, \eta_r)$ is not a fixed value and having a specified interval between 0 and 1. The parameters η_l and η_r depicts the periphery of T-2TFV. Intuitionally, if $\eta_l = \eta_r = 0$, then T-2TFV $\widetilde{\psi}$ changes into a TFV and, Eqs. (1) and (2) represents the membership function of TFV. With the aid of Eqs. (1) and (2), $\widetilde{\mu}_{\widetilde{\psi}}(x)$ can be depicted as follows:

$$\widetilde{\mu}_{\widetilde{\psi}}(x) = \begin{cases} \left[\frac{x - s_1}{s_2 - s_1} - \eta_l \frac{x - s_1}{s_2 - s_1}, \frac{x - s_1}{s_2 - s_1}, \frac{x - s_1}{s_2 - s_1} + \eta_r \frac{x - s_1}{s_2 - s_1}\right], & \text{if } s_1 \le x \le \frac{s_1 + s_2}{2}, \\ \left[\frac{x - s_1}{s_2 - s_1} - \eta_l \frac{s_2 - x}{s_2 - s_1}, \frac{x - s_1}{s_2 - s_1}, \frac{x - s_1}{s_2 - s_1} + \eta_r \frac{s_2 - x}{s_2 - s_1}\right], & \text{if } \frac{s_1 + s_2}{2} \le x \le s_2, \\ \left[\frac{s_3 - x}{s_3 - s_2} - \eta_l \frac{x - s_2}{s_3 - s_2}, \frac{s_3 - x}{s_3 - s_2}, \frac{s_3 - x}{s_3 - s_2} + \eta_r \frac{x - s_2}{s_3 - s_2}\right], & \text{if } s_2 \le x \le \frac{s_2 + s_3}{2}, \\ \left[\frac{s_3 - x}{s_3 - s_2} - \eta_l \frac{s_3 - x}{s_3 - s_2}, \frac{s_3 - x}{s_3 - s_2}, \frac{s_3 - x}{s_3 - s_2} + \eta_r \frac{s_3 - x}{s_3 - s_2}\right], & \text{if } \frac{s_2 + s_3}{2} \le x \le s_3, \end{cases}$$

Thus, the T-2TFV $\widetilde{\psi}$ is represented by $\widetilde{\psi} = (s_1, s_2, s_3; \eta_l, \eta_r)$. For instance, suppose a T-2TFV $\widetilde{\psi} = (2, 3, 4; 0.5, 0.8)$ then its type-2 membership function can be depicted as follows:

$$\widetilde{\mu}_{\widetilde{\psi}}(x) = \begin{cases} (0.5(x-2), x-2, 1.8(x-2)), & \text{if } 2 \le x \le 2.5, \\ ((x-2) - 0.5(3-x), x-2, (x-2) + 0.8(3-x)), & \text{if } 2.5 \le x \le 3, \\ ((4-x) - 0.5(x-3), 4-x, (4-x) + 0.8(x-3)), & \text{if } 3 \le x \le 3.5, \\ (0.5(4-x), 4-x, 1.8(4-x)), & \text{if } 3.5 \le x \le 4. \end{cases}$$

Hence the membership function for each point of x is a TFV, e.g., $\widetilde{\mu}_{\widetilde{\psi}}(2.5) = (0.25, 0.5, 0.9)$, $\widetilde{\mu}_{\widetilde{\psi}}(3.2) = (0.7, 0.8, 0.96)$, and so on. The domain of type-2 membership function $\widetilde{\mu}_{\widetilde{\psi}}(2.5)$, i.e., $V_{2.5}$ ranges from 0.25 to 0.9 and $\widetilde{\mu}_{\widetilde{\psi}}(3.2)$ ranges from 0.7 to 0.96, respectively. The domain of type-2 membership function of all the elements elicit the FOU.

Definition 4 (*Critical values for random fuzzy variables*) Qin et al. [26] investigated three types of critical values (CV) of a random fuzzy variable $\widetilde{\psi}$. They can be summarized as follows:

(i) the optimistic CV of $\widetilde{\psi}$, represented by $\overline{CV}(\widetilde{\psi})$, is depicted as

$$\overline{CV}(\widetilde{\psi}) = \sup_{\alpha \in [0,1]} \left[\alpha \cap \text{Pos}\left(\widetilde{\psi} \ge \alpha\right)\right] \quad (3)$$

(ii) the pessimistic CV of $\widetilde{\psi}$, represented by $\underline{CV}(\widetilde{\psi})$, is depicted as

$$\underline{CV}(\widetilde{\psi}) = \sup_{\alpha \in [0,1]} \left[\alpha \cap \text{Nec}\left(\widetilde{\psi} \ge \alpha\right)\right] \quad (4)$$

(iii) the CV of $\widetilde{\psi}$, represented by $CV(\widetilde{\psi})$, is depicted as

$$CV(\widetilde{\psi}) = \sup_{\alpha \in [0,1]} \left[\alpha \cap \text{Cr}\left(\widetilde{\psi} \ge \alpha\right)\right], \quad (5)$$

2.1 Reduction Method for T-2FVs Based on CV

Firstly, Qin et al. [26] propounded a reduction method based on CV that transforms a type-2 fuzzy variable into a type-1 fuzzy variable (or simply a fuzzy variable). Suppose $\widetilde{\psi}$ be a type-2 fuzzy variable with type-2 membership function $\widetilde{\mu}_{\widetilde{\psi}}(x)$ (a random fuzzy variable). Here, we tried to incorporate the CVs as a depicting value for random fuzzy variable $\widetilde{\mu}_{\widetilde{\psi}}(x)$, i.e., $\overline{CV}(\widetilde{\psi})$, $\underline{CV}(\widetilde{\psi})$, and $CV(\widetilde{\psi})$. Thus these methods of reduction are known as optimistic CV reduction, pessimistic CV reduction, and CV reduction methods, respectively.

Example 2 Suppose a type-2 fuzzy variable $\widetilde{A}$. With the aid of Eq. (3), we have $\overline{CV}(\widetilde{\mu}_{\widetilde{A}}(4)) = \sup_{\alpha\in[0,\,1]}\left[\alpha \cap \mathrm{Pos}\left(\widetilde{\mu}_{\widetilde{A}}(4) \geq \alpha\right)\right]$, where

$$\mathrm{Pos}\left(\widetilde{\mu}_{\widetilde{A}}(4) \geq \alpha\right) = \begin{cases} 1, & \text{if } \alpha \leq 0.4, \\ 0.7, & \text{if } 0.4 \leq \alpha \leq 0.6 \\ 0, & \text{if } 0.6 \leq \alpha \leq 1. \end{cases}$$

such that

$$\begin{aligned}\overline{CV}(\widetilde{\mu}_{\widetilde{A}}(4)) &= \sup_{\alpha\in[0,\,0.4]}[\alpha \cap 1] \cup \sup_{\alpha\in[0.4,\,0.6]}[\alpha \cap 0.7] \\ &\quad \cup \sup_{\alpha\in[0.6,\,1]}[\alpha \cap 0] \\ &= 0.4 \cup 0.6 \cup 0 = 0.6\end{aligned}$$

Similarly, using Eqs. (3), (4), and (5), we have

$\overline{CV}(\widetilde{\mu}_{\widetilde{A}}(4)) = 0.6$, $\overline{CV}(\widetilde{\mu}_{\widetilde{A}}(5)) = 0.8$,
$\overline{CV}(\widetilde{\mu}_{\widetilde{A}}(6)) = 0.6$
$\underline{CV}(\widetilde{\mu}_{\widetilde{A}}(4)) = 0.4$, $\underline{CV}(\widetilde{\mu}_{\widetilde{A}}(5)) = 0.6$,
$\underline{CV}(\widetilde{\mu}_{\widetilde{A}}(6)) = 0.6$
$CV(\widetilde{\mu}_{\widetilde{A}}(4)) = 0.4$, $CV(\widetilde{\mu}_{\widetilde{A}}(5)) = 0.65$,
$CV(\widetilde{\mu}_{\widetilde{A}}(6)) = 0.6$

On implementing optimistic CV, pessimistic CV and CV reduction methods, the type-2 fuzzy variable $\widetilde{A}$ deduced into the following fuzzy variables $\begin{pmatrix} 4,\,5,\,6 \\ 0.6,\,0.8,\,0.6 \end{pmatrix}$, $\begin{pmatrix} 4,\,5,\,6 \\ 0.4,\,0.6,\,0.6 \end{pmatrix}$ and $\begin{pmatrix} 4,\,5,\,6 \\ 0.4,\,0.65,\,0.6 \end{pmatrix}$.

Theorem 1 [26] *Consider a T-2TFV $\widetilde{\psi} = (s_1, s_2, s_3; \eta_l, \eta_r)$, then we have*

(i) *Using the optimistic CV reduction method, the reduction ψ_1 of $\widetilde{\psi}$ has the following possibility distribution*

$$\mu_{\psi_1}(x) = \begin{cases} \dfrac{(1+\eta_r)(x-s_1)}{s_2-s_1+\eta_r(x-s_1)}, & \text{if } s_1 \leq x \leq \dfrac{s_1+s_2}{2}, \\ \dfrac{(1+\eta_r)x+\eta_r s_2-s_1}{s_2-s_1+\eta_r(s_2-x)}, & \text{if } \dfrac{s_1+s_2}{2} \leq x \leq s_2, \\ \dfrac{(-1+\eta_r)x-\eta_r s_2-s_3}{s_3-s_2+\eta_r(x-s_2)}, & \text{if } s_2 \leq x \leq \dfrac{s_2+s_3}{2}, \\ \dfrac{(1+\eta_r)(s_3-x)}{s_3-s_2+\eta_r(s_3-x)}, & \text{if } \dfrac{s_2+s_3}{2} \leq x \leq s_3, \end{cases} \tag{6}$$

(ii) *Using the pessimistic CV reduction method, the reduction ψ_2 of $\widetilde{\psi}$ has the following possibility distribution*

$$\mu_{\psi_2}(x) = \begin{cases} \dfrac{(x-s_1)}{s_2-s_1+\eta_l(x-s_1)}, & \text{if } s_1 \leq x \leq \dfrac{s_1+s_2}{2}, \\ \dfrac{(x-s_1)}{s_2-s_1+\eta_l(s_2-x)}, & \text{if } \dfrac{s_1+s_2}{2} \leq x \leq s_2, \\ \dfrac{(s_3-x)}{s_3-s_2+\eta_l(x-s_2)}, & \text{if } s_2 \leq x \leq \dfrac{s_2+s_3}{2}, \\ \dfrac{(s_3-x)}{s_3-s_2+\eta_l(s_3-x)}, & \text{if } \dfrac{s_2+s_3}{2} \leq x \leq s_3, \end{cases} \tag{7}$$

(iii) *Using the CV reduction method, the reduction ψ_3 of $\widetilde{\psi}$ has the following possibility distribution*

$$\mu_{\psi_3}(x) = \begin{cases} \dfrac{(1+\eta_r)(x-s_1)}{s_2-s_1+2\eta_r(x-s_1)}, & \text{if } s_1 \leq x \leq \dfrac{s_1+s_2}{2}, \\ \dfrac{(1-\eta_l)x+\eta_l s_2-s_1}{s_2-s_1+2\eta_l(s_2-x)}, & \text{if } \dfrac{s_1+s_2}{2} \leq x \leq s_2, \\ \dfrac{(-1+\eta_l)x-\eta_l s_2-s_3}{s_3-s_2+2\eta_l(x-s_2)}, & \text{if } s_2 \leq x \leq \dfrac{s_2+s_3}{2}, \\ \dfrac{(1+\eta_r)(s_3-x)}{s_3-s_2+2\eta_r(s_3-x)}, & \text{if } \dfrac{s_2+s_3}{2} \leq x \leq s_3, \end{cases} \tag{8}$$

Theorem 2 *(Qin et al. [26]) Consider ψ_i be the reduction of the type-2 fuzzy variable $\widetilde{\psi}_i = (s_1^i, s_2^i, s_3^i; \eta_{l,i}, \eta_{r,i})$ derived from the CV reduction method for $i = 1, 2, \ldots, n$. Also, let $\psi_1, \psi_2, \ldots, \psi_n$ are mutually independent, and $k_i \geq 0$ for all $i = 1, 2, \ldots, n$.*

Proof Please visit [26]. □

2.2 Nearest Interval Approximation of Continuous T-2FVs

The nearest interval approximation method provides the crisp interval for a continuous T-2FVs. To present this, we first obtain the CV-based reduction of the T-2FVs. After that, we determine the corresponding α-cuts of these CV-based reductions. Ultimately, on applying interval approximation method to the α-cuts, we get the approximate crisp intervals.

Here, we demonstrate the nearest interval approximation method with T-2FV. Suppose there be a T-2FV $\widetilde{\psi} = (s_1, s_2, s_3; \eta_l, \eta_r)$. Using Theorem 1, we have the optimistic CV reduction, pessimistic CV reduction, and CV reduction of $\widetilde{\psi}$ as ψ_1, ψ_2 and ψ_3 with possibility distribution functions depicted by Eqs. (6)–(8). Applying the concept of α-cuts of a fuzzy variable Wu and Mendel [33], we obtain the α-cuts of the reductions of $\widetilde{\psi}$.

α-cut of the optimistic CV reduction ψ_1 of $\widetilde{\psi}$: Using the definition of α-cut of a fuzzy variable, we get the α-cut of the reduction ψ_1 as $[\psi_{1L}(\alpha), \psi_{1R}(\alpha)]$, where

$$\psi_{1L}(\alpha) = \begin{cases} \dfrac{(1+\eta_r)s_1 + (s_2 - s_1 - \eta_r s_1)\alpha}{(1+\eta_r) - \eta_r\alpha}, & \text{if } 0 \le \alpha \le 0.5, \\ \dfrac{(s_1 - \eta_r s_2) + (s_2 - s_1 + \eta_r s_2)\alpha}{(1-\eta_r) + \eta_r\alpha}, & \text{if } 0.5 \le \alpha \le 1 \end{cases} \tag{9}$$

$$\psi_{1R}(\alpha) = \begin{cases} \dfrac{(s_3 - \eta_r s_2) - (s_3 - s_2 - \eta_r s_2)\alpha}{(1-\eta_r) + \eta_r\alpha}, & \text{if } 0.5 \le \alpha \le 1, \\ \dfrac{(1+\eta_r)s_3 - (s_3 - s_2 + \eta_r s_3)\alpha}{(1+\eta_r) - \eta_r\alpha}, & \text{if } 0 \le \alpha \le 0.5 \end{cases} \tag{10}$$

α-cut of the pessimistic CV reduction ψ_2 of $\widetilde{\psi}$: The α-cut of the reduction ψ_2 is determined as $[\psi_{2L}(\alpha), \psi_{2R}(\alpha)]$, where

$$\psi_{2L}(\alpha) = \begin{cases} \dfrac{s_1 + (s_2 - s_1 - \eta_l s_1)\alpha}{1 - \eta_l\alpha}, & \text{if } 0 \le \alpha \le 0.5, \\ \dfrac{s_1 + (s_2 - s_1 + \eta_l s_2)\alpha}{1 + \eta_l\alpha}, & \text{if } 0.5 \le \alpha \le 1 \end{cases} \tag{11}$$

$$\psi_{2R}(\alpha) = \begin{cases} \dfrac{s_3 - (s_3 - s_2 - \eta_l s_2)\alpha}{1 + \eta_l\alpha}, & \text{if } 0.5 \le \alpha \le 1, \\ \dfrac{s_3 - (s_3 - s_2 + \eta_l s_3)\alpha}{1 - \eta_l\alpha}, & \text{if } 0 \le \alpha \le 0.5 \end{cases} \tag{12}$$

α-cut of the CV reduction ψ_3 of $\widetilde{\psi}$: The α-cut of the reduction ψ_3 is determined as $[\psi_{3L}(\alpha), \psi_{3R}(\alpha)]$, where

$$\psi_{3L}(\alpha) = \begin{cases} \dfrac{(1+\eta_r)s_1 + (s_2 - s_1 - 2\eta_r s_1)\alpha}{(1+\eta_r) - 2\eta_r\alpha}, & \text{if } 0 \le \alpha \le 0.5, \\ \dfrac{(s_1 - \eta_l s_2) + (s_2 - s_1 + 2\eta_l s_2)\alpha}{(1-\eta_l) + 2\eta_l\alpha}, & \text{if } 0.5 \le \alpha \le 1 \end{cases} \tag{13}$$

$$\psi_{3R}(\alpha) = \begin{cases} \dfrac{(s_3 - \eta_l s_2) - (s_3 - s_2 - 2\eta_l s_2)\alpha}{(1-\eta_l) + 2\eta_l\alpha}, & \text{if } 0.5 \le \alpha \le 1, \\ \dfrac{(1+\eta_r)s_3 - (s_3 - s_2 + 2\eta_r s_3)\alpha}{(1+\eta_r) - 2\eta_r\alpha}, & \text{if } 0 \le \alpha \le 0.5 \end{cases} \tag{14}$$

It is well-known that nearest interval approximation of a fuzzy number [21] $\widetilde{A}$ with the distance metric d is represented by $C_d(\widetilde{A}) = [C_L, C_R]$, such that $C_L = \int_0^1 A_L(\alpha)\mathrm{d}\alpha$ and $C_R = \int_0^1 A_R(\alpha)\mathrm{d}\alpha$, where distance metric d measure the distance of $\widetilde{A}$ from $C_d(\widetilde{A})$ and can be depicted as follows:

$$d\left(\widetilde{A}, C_d(\widetilde{A})\right) = \sqrt{\int_0^1 (A_L(\alpha) - C_L)^2\mathrm{d}\alpha + \int_0^1 (A_R(\alpha) - C_R)^2\mathrm{d}\alpha}$$

Applying this method for the α-cuts of optimistic CV, pessimistic CV and CV reduction of $\widetilde{\psi}$, we can obtain the nearest interval approximation of $\widetilde{\psi}$.

Nearest interval approximation of $\widetilde{\psi}$ using α-cut of the optimistic CV reduction ψ_1 of $\widetilde{\psi}$: For this, the nearest interval approximation of $\widetilde{\psi}$ can be stated as $[C_L, C_R]$ follows:

$$\begin{aligned} C_L &= \int_0^1 \psi_{1L} d(\alpha) \\ &= \int_0^{0.5} \frac{(1+\eta_r)s_1 + (s_2 - s_1 - \eta_r s_1)\alpha}{(1+\eta_r) - \eta_r\alpha} d(\alpha) \\ &\quad + \int_{0.5}^1 \frac{(s_1 - \eta_r s_2) + (s_2 - s_1 + \eta_r s_2)\alpha}{(1-\eta_r) + \eta_r\alpha} d(\alpha) \\ &= C_{L1} + C_{L2} \\ C_{L1} &= \frac{(1+\eta_r)s_1}{\eta_r} \ln\left(\frac{1+\eta_r}{1+0.5\eta_r}\right) \\ &\quad - \frac{s_2 - s_1 - \eta_r s_1}{\eta_r^2}\left[0.5\eta_r - (1+\eta_r)\ln\left(\frac{1+\eta_r}{1+0.5\eta_r}\right)\right] \\ C_{L2} &= -\frac{s_1 - \eta_r s_2}{\eta_r}\ln(1 - 0.5\eta_r) \\ &\quad + \frac{s_2 - s_1 + \eta_r s_2}{\eta_r^2}[0.5\eta_r + (1-\eta_r)\ln(1 - 0.5\eta_r)] \end{aligned} \tag{15}$$

$$
\begin{aligned}
C_R &= \int_0^1 \psi_{1R} d(\alpha) \\
&= \int_0^{0.5} \frac{(1+\eta_r)s_3 - (s_3 - s_2 + \eta_r s_3)\alpha}{(1+\eta_r) - \eta_r \alpha} d(\alpha) \\
&\quad + \int_{0.5}^1 \frac{(s_3 - \eta_r s_2) - (s_3 - s_2 - \eta_r s_2)\alpha}{(1-\eta_r) + \eta_r \alpha} d(\alpha) \\
&= C_{R1} + C_{R2} \\
C_{R1} &= \frac{(1+\eta_r)s_3}{\eta_r} \\
&\quad \times \ln\left(\frac{1+\eta_r}{1+0.5\eta_r}\right) \\
&\quad + \frac{s_3 - s_2 - \eta_r s_3}{\eta_r^2}\left[0.5\eta_r - (1+\eta_r)\ln\left(\frac{1+\eta_r}{1+0.5\eta_r}\right)\right] \\
C_{R2} &= -\frac{s_3 - \eta_r s_2}{\eta_r} \\
&\quad \times \ln(1-0.5\eta_r) - \frac{s_3 - s_2 + \eta_r s_2}{\eta_r^2} \\
&\quad \times [0.5\eta_r + (1-\eta_r)\ln(1-0.5\eta_r)]
\end{aligned} \tag{16}
$$

The intervals given by Eqs. (15) and (16) are called optimistic nearest interval approximation of $\widetilde{\psi}$.

Nearest interval approximation of $\widetilde{\psi}$ using α-cut of the pessimistic CV reduction ψ_2 of $\widetilde{\psi}$: In this case, the nearest interval approximation of $\widetilde{\psi}$ can be stated as $[C_L, C_R]$ follows:

$$
\begin{aligned}
C_L &= \int_0^1 \psi_{2L} d(\alpha) \\
&= \int_0^{0.5} \frac{s_1 + (s_2 - s_1 - \eta_l s_1)\alpha}{1 - \eta_l \alpha} d(\alpha) \\
&\quad + \int_{0.5}^1 \frac{s_1 + (s_2 - s_1 + \eta_l s_2)\alpha}{1 + \eta_l \alpha} d(\alpha) \\
&= C_{L1} + C_{L2} \\
C_{L1} &= -\frac{s_1}{\eta_l} \\
&\quad \times \ln(1-0.5\eta_l) - \frac{s_2 - s_1 - \eta_l s_1}{\eta_l^2} \\
&\quad \times [0.5\eta_l + \ln(1-0.5\eta_r)] \\
C_{L2} &= \frac{s_1}{\eta_l}\ln\left(\frac{1+\eta_l}{1+0.5\eta_l}\right) \\
&\quad + \frac{s_2 - s_1 + \eta_r s_2}{\eta_r^2} \\
&\quad \times \left[0.5\eta_l - \ln\left(\frac{1+\eta_l}{1+0.5\eta_l}\right)\right]
\end{aligned} \tag{17}
$$

$$
\begin{aligned}
C_R &= \int_0^1 \psi_{2R} d(\alpha) \\
&= \int_0^{0.5} \frac{s_3 - (s_3 - s_2 + \eta_l s_3)\alpha}{1 - \eta_l \alpha} d(\alpha) \\
&\quad + \int_{0.5}^1 \frac{s_3 - (s_3 - s_2 - \eta_l s_2)\alpha}{1 + \eta_l \alpha} d(\alpha) \\
&= C_{R1} + C_{R2} \\
C_{R1} &= -\frac{s_3}{\eta_l}\ln(1-0.5\eta_l) \\
&\quad + \frac{s_3 - s_2 + \eta_l s_3}{\eta_l^2} \\
&\quad [0.5\eta_l + \ln(1-0.5\eta_l)] \\
C_{R2} &= \frac{s_3}{\eta_l}\ln\left(\frac{1+\eta_l}{1+0.5\eta_l}\right) \\
&\quad - \frac{s_3 - s_2 + \eta_l s_2}{\eta_r^l}\left[0.5\eta_l - \ln\left(\frac{1+\eta_l}{1+0.5\eta_l}\right)\right] s
\end{aligned} \tag{18}
$$

The intervals given by Eqs. (17) and (18) are called pessimistic nearest interval approximation of $\widetilde{\psi}$.

Nearest interval approximation of $\widetilde{\psi}$ using α-cut of the CV reduction ψ_3 of $\widetilde{\psi}$: In this case, the nearest interval approximation of $\widetilde{\psi}$ can be stated as $[C_L, C_R]$ follows:

$$
\begin{aligned}
C_L &= \int_0^1 \psi_{3L} d(\alpha) \\
&= \int_0^{0.5} \frac{(1+\eta_r)s_1 + (s_2 - s_1 - 2\eta_r s_1)\alpha}{(1+\eta_r) - 2\eta_r \alpha} d(\alpha) \\
&\quad + \int_{0.5}^1 \frac{(s_1 - \eta_l s_2) + (s_2 - s_1 + 2\eta_l s_2)\alpha}{(1-\eta_l) + 2\eta_l \alpha} d(\alpha) \\
&= C_{L1} + C_{L2} \\
C_{L1} &= \frac{(1+\eta_r)s_1}{\eta_r} \\
&\quad \times \ln(1+\eta_r) - \frac{s_2 - s_1 - 2\eta_r s_1}{4\eta_r^2} \\
&\quad \times [\eta_r - (1+\eta_r)\ln(1+\eta_r)] \\
C_{L2} &= \frac{s_1 - \eta_l s_2}{2\eta_l}\ln(1+\eta_l) \\
&\quad + \frac{s_2 - s_1 + 2\eta_l s_2}{4\eta_l^2}[\eta_l - (1-\eta_l)\ln(1+\eta_l)]
\end{aligned} \tag{19}
$$

$$\begin{aligned} C_R &= \int_0^1 \psi_{3R} d(\alpha) \\ &= \int_0^{0.5} \frac{(1+\eta_r)s_3 - (s_3 - s_2 + 2\eta_r s_3)\alpha}{(1+\eta_r) - 2\eta_r \alpha} d(\alpha) \\ &\quad + \int_{0.5}^1 \frac{(s_3 - \eta_l s_2) - (s_3 - s_2 - 2\eta_l s_2)\alpha}{(1-\eta_l) + 2\eta_l \alpha} d(\alpha) \\ &= C_{R1} + C_{R2} \\ C_{R1} &= \frac{(1+\eta_r)s_3}{\eta_r} \\ &\quad \times \ln(1+\eta_r) - \frac{s_3 - s_2 + 2\eta_r s_3}{4\eta_r^2} \\ &\quad \times [\eta_r - (1+\eta_r)\ln(1+\eta_r)] \\ C_{R2} &= \frac{s_3 - \eta_l s_2}{2\eta_l} \ln(1+\eta_l) \\ &\quad + \frac{s_3 - s_2 - 2\eta_l s_2}{4\eta_l^2} [\eta_l - (1-\eta_l)\ln(1+\eta_l)] \end{aligned} \tag{20}$$

The intervals given by Eqs. (19) and (20) are called credibilistic nearest interval approximation of $\widetilde{\psi}$.

Example 3 Suppose a T-2TFV $\widetilde{\psi} = (2,3,4;0.5,0.8)$, then we can obtain the nearest interval approximation of $\widetilde{\psi}$. Taking the advantage of Eqs. (15) and (16) the optimistic, Eqs. (17) and (18) the pessimistic and Eqs. (19) and (20) the credibilistic nearest interval approximation of $\widetilde{\psi}$ are depicted as $[2.4086, 3.5913]$, $[2.5567, 3.4432]$ and $[2.4925, 3.504]$, respectively.

3 Supplier Selection Problem

The multiobjective SSP is considered under the uncertain situation. It is assumed that an automobile company places an ordered quantity to the different suppliers for multiple parts to identify the quota allocation in a supply chain. For this purpose, the decision-makers are strictly against the shortage of parts, specific with the different capacities and budget allocation. Due to real-life complexity, vagueness and ambiguousness among the parameters are taken as type-2 triangular fuzzy numbers, which is more realistic. The decision-makers' main aim is to handle the T-2TF parameters so that the minimum total cost associated with ordering the aggregate demand, the rejected items of the suppliers, and the late delivered items are obtained. The relevant notions and descriptions are summarized in Table 1.

Objective functions

The total cost of ordering in SSP has significant importance while allocating the budgets. For minimizing the total cost for ordering the aggregate demand, the first objective function is depicted. Mathematically, it can be shown in Eq. (21).

$$\text{Minimize } O_1 = \sum_i \sum_j y_i^j \times \left(\widetilde{P}_i^j \times x_i^j\right) \quad \forall i,j. \tag{21}$$

The second objective function represents the total rejection while handling the items. Thus, the second objective function ensures the minimization of the vendors' total rejected items over a planning period. The mathematical

Table 1 Notions and descriptions

Indices	Descriptions
i	Denotes the number of suppliers $(i = 1, 2, \ldots, I)$
j	Denotes the number of items $(j = 1, 2, \ldots, J)$
Decision variable	
x_i^j	Units order quantity assigned to supplier i
y_i^j	Represents the binary variable such that $y_i^j = \begin{cases} 1, & \text{if } x_i^j > 0 \\ 0, & \text{if otherwise} \end{cases}$
Parameters	
$\widetilde{TD}^j$	Total aggregate demand quantity of item type j over a fixed planning period (units)
$\widetilde{P}_i^j$	Price of unit item type j of the ordered quantity to the supplier i ($/unit)
$\widetilde{R}_i^j$	Percentage of rejected items j delivered by the supplier i
$\widetilde{LD}_i^j$	Percentage of late delivered items j by the supplier i
$\widetilde{UL}_i^j$	Maximum limit of available quantity of item type j for the supplier i (units)
$\widetilde{RV}_i$	Rating value for supplier i
$\widetilde{PC}$	Minimum purchasing value that a vendor can have
$\widetilde{QF}_i$	Quota flexibility value for supplier i
$\widetilde{S}$	Minimum flexibility value in supply quota that a vendor should have
$\widetilde{B}_i$	Total budget allocation to the supplier i ($)

expression for the total rejected items is presented in Eq. (22).

$$\text{Minimize } O_2 = \sum_i \sum_j y_i^j \times \left(\widetilde{R}_i^j \times x_i^j\right) \quad \forall i,j. \tag{22}$$

To survive in the competitive market, on-time delivery of the items is an essential criterion for the suppliers. It enhances the market values and good-will of the vendors. Hence, the third objective function minimizes the total of late delivered items of the suppliers. The mathematical expression for the minimization of late delivery is stated in Eq. (23).

$$\text{Minimize } O_3 = \sum_i \sum_j y_i^j \times \left(\widetilde{LD}_i^j \times x_i^j\right) \quad \forall i,j. \tag{23}$$

Constraints

The aggregated demand of the item type j from each supplier i must be fulfilled; and can be represented in constraint (24).

$$\sum_i \sum_j y_i^j \times x_i^j = \widetilde{TD}^j \quad \forall i,j. \tag{24}$$

The constraint (25) ensures that the available maximum capacity of item type j must be less than the ordered quantity given to the supplier i.

$$\sum_i \sum_j y_i^j \times x_i^j \le \widetilde{UL}^i \quad \forall i,j. \tag{25}$$

The total purchasing value of item type j is represented in constraint (26).

$$\sum_i \sum_j y_i^j \times \left(\widetilde{RV}_i \times x_i^j\right) \ge \widetilde{PC} \quad \forall i,j. \tag{26}$$

The constraint (27) provides the essential flexibility needed with vendors' quota.

$$\sum_i \sum_j y_i^j \times \left(\widetilde{QF}_i \times x_i^j\right) \le \widetilde{S} \quad \forall i,j. \tag{27}$$

The restrictions over maximum budget amount allocated to suppliers is represented by constraint (28).

$$\sum_i \sum_j y_i^j \times \left(\widetilde{P}_i^j \times x_i^j\right) \le \widetilde{B}_i \quad \forall i,j. \tag{28}$$

The constraints (29) reveal the flow status of items.

$$x_i^j = \left\{y_i^j = 1 \text{ or } 0\right\} \quad \forall i,j. \tag{29}$$

The non-negativity restrictions over ordered quantity given to suppliers is represented in constraint (30).

$$x_i^j \ge 0 \quad \forall i,j. \tag{30}$$

Thus the formulation of SSP with type-2 fuzzy parameters can be summarized as follows (31):

$$\begin{aligned}
&\text{Minimize } O_1 = \textstyle\sum_i \sum_j y_i^j \times \left(\widetilde{P}_i^j \times x_i^j\right)\\
&\text{Minimize } O_2 = \textstyle\sum_i \sum_j y_i^j \times \left(\widetilde{R}_i^j \times x_i^j\right)\\
&\text{Minimize } O_3 = \textstyle\sum_i \sum_j y_i^j \times \left(\widetilde{LD}_i^j \times x_i^j\right)\\
&\text{subject to}\\
&\qquad \textstyle\sum_i \sum_j y_i^j \times x_i^j = \widetilde{TD}^j\\
&\qquad \textstyle\sum_i \sum_j y_i^j \times x_i^j \le \widetilde{UL}^i\\
&\qquad \textstyle\sum_i \sum_j y_i^j \times \left(\widetilde{RV}_i \times x_i^j\right) \ge \widetilde{PC}\\
&\qquad \textstyle\sum_i \sum_j y_i^j \times \left(\widetilde{QF}_i \times x_i^j\right) \le \widetilde{S}\\
&\qquad \textstyle\sum_i \sum_j y_i^j \times \left(\widetilde{P}_i^j \times x_i^j\right) \le \widetilde{B}_i\\
&\qquad x_i^j = \left\{y_i^j = 1 \text{ or } 0\right\}\\
&\qquad x_i^j \ge 0.
\end{aligned} \tag{31}$$

where $\widetilde{(\cdot)}$, $(\cdot = TD, P, R, LD, UL, RV, PC, QF, S, B)$ represent the type-2 triangular fuzzy parameters involved in the objective functions and constraints, respectively. The transformation of SSP into its deterministic form can be presented in the following sub-sections:

3.1 Chance-Constrained Programming Problem Using Generalized Credibility

Let us consider that all the type-2 triangular fuzzy parameters $\widetilde{(\cdot)}$ are transformed into the equivalent type-1 fuzzy (or only fuzzy) parameters $\widetilde{(\cdot')}$ using the CV-based reduction method. To solve the proposed SSP with type-2 fuzzy parameters, we present a chance-constrained programming (CCP) model with these reduced fuzzy parameters. The working principle of chance-constrained programming is based on the chance (or confidence) level associated with the risk violation. In CCP, the vague or uncertain constraints are permitted to be violated such that it must be satisfied at some confidence level (or chances). Firstly, the CCP with type-1 (fuzzy) parameters was introduced by Liu and Chen [18], Mendel and John [21], Yang and Liu [35] using credibility-based measures. Since the transformed fuzzy parameters $\widetilde{(\cdot')}$ may not be normalized, hence the actual credibility measure cannot be applied. Therefore, with the aid of generalized credibility measures, as the multiobjective SSP (31) is of minimization-type problem, the equivalent CCP model can be formulated of the SSP (31) as follows:

$$\begin{aligned}
&\mathrm{Min}_x(\mathrm{Min}_{\tilde{z}_1}\tilde{z}_1) = \widetilde{Cr}\left[\sum_i\sum_j y_i^j \times \left(\widetilde{P'}_i^j \times x_i^j\right) \le \tilde{z}_1\right] \ge \alpha\\
&\mathrm{Min}_x(\mathrm{Min}_{\tilde{z}_2}\tilde{z}_2) = \widetilde{Cr}\left[\sum_i\sum_j y_i^j \times \left(\widetilde{R'}_i^j \times x_i^j\right) \le \tilde{z}_2\right] \ge \alpha\\
&\mathrm{Min}_x(\mathrm{Min}_{\tilde{z}_3}\tilde{z}_3) = \widetilde{Cr}\left[\sum_i\sum_j y_i^j \times \left(\widetilde{LD'}_i^j \times x_i^j\right) \le \tilde{z}_3\right] \ge \alpha\\
&\text{subject to}\\
&\widetilde{Cr}\left[\sum_i\sum_j y_i^j \times x_i^j = \widetilde{TD'}^j\right] \ge \alpha_{i1}^j\\
&\widetilde{Cr}\left[\sum_i\sum_j y_i^j \times x_i^j \le \widetilde{UL'}^i\right] \ge \alpha_{i2}^j\\
&\widetilde{Cr}\left[\sum_i\sum_j y_i^j \times \left(\widetilde{RV'}_i \times x_i^j\right) \ge \widetilde{PC'}\right] \ge \alpha_{i3}^j\\
&\widetilde{Cr}\left[\sum_i\sum_j y_i^j \times \left(\widetilde{QF'}_i \times x_i^j\right) \le \tilde{S'}\right] \ge \alpha_{i4}^j\\
&\widetilde{Cr}\left[\sum_i\sum_j y_i^j \times \left(\widetilde{P'}_i^j \times x_i^j\right) \le \widetilde{B'}_i\right] \ge \alpha_{i5}^j\\
&x_i^j = \{y_i^j = 1 \text{ or } 0\}\\
&x_i^j \ge 0.
\end{aligned} \tag{32}$$

where $\mathrm{Min}\tilde{z}_\cdot$ represent the minimum possible deterministic form that the objective function attains with generalized credibility at least $\alpha(0 \le \alpha \le 1)$. More precisely, α corresponds to the minimization of the α-critical value Mendel and John [21] of the objective functions. Further, $\alpha_{i\cdot}^j(0 \le \alpha_{i\cdot}^j \le 1)$ are the pre-determined generalized credibility satisfaction levels of the respective constraints for all i, j, respectively. All the constraints signify that the restriction imposed over ordered quantity of items type j given to supplier i must be satisfied at the credibility level by at least $\alpha_{i\cdot}^j$.

3.1.1 Crisp Equivalance

Suppose that $\widetilde{(\cdot)}$ are mutually independent the type-2 triangular fuzzy variables depicted as $\widetilde{(\cdot)} = \left((\cdot)^1, (\cdot)^2, (\cdot)^3; \eta_{l,\cdot}, \eta_{r,\cdot}\right)$. Using Theorem 2, the chance-constrained SSP model (32) is transformed into the following deterministic equivalent parametric programming problems:

Case I When $0 \le \alpha \le 0.25$, the equivalent parametric programming problem for model (32) is given as follows (33):

$$\begin{aligned}
&\text{Minimize } O_1 = \sum_i\sum_j y_i^j \times \left[\frac{\left(1-2\alpha+(1-4\alpha)\eta_{r,i}^j\right)P_i^{1j}x_i^j + 2\alpha P_i^{2j}x_i^j}{1+(1-4\alpha)\eta_{r,i}^j}\right]\\
&\text{Minimize } O_2 = \sum_i\sum_j y_i^j \times \left[\frac{\left(1-2\alpha+(1-4\alpha)\eta_{r,i}^j\right)R_i^{1j}x_i^j + 2\alpha R_i^{2j}x_i^j}{1+(1-4\alpha)\eta_{r,i}^j}\right]\\
&\text{Minimize } O_3 = \sum_i\sum_j y_i^j \times \left[\frac{\left(1-2\alpha+(1-4\alpha)\eta_{r,i}^j\right)LD_i^{1j}x_i^j + 2\alpha LD_i^{2j}x_i^j}{1+(1-4\alpha)\eta_{r,i}^j}\right]\\
&\text{subject to}\\
&\sum_i\sum_j y_i^j \times x_i^j = D_{TD^j}\\
&\sum_i\sum_j y_i^j \times x_i^j \le D_{UL^i}\\
&sum_i\sum_j y_i^j \times \left(D_{RV^i} \times x_i^j\right) \ge D_{PC}\\
&\sum_i\sum_j y_i^j \times \left(D_{QF^i} \times x_i^j\right) \le D_S\\
&\sum_i\sum_j y_i^j \times \left(D_{P_i^j} \times x_i^j\right) \le D_{B_i}\\
&x_i^j = \{y_i^j = 1 \text{ or } 0\}\\
&; x_i^j \ge 0.
\end{aligned} \tag{33}$$

where $D_{TD^j}, D_{UL^i}, D_{RV^i}, D_{PC}, D_{QF^i}, D_S, D_{P_i^j}, D_{B_i}$ are depicted in Eqs. (37)–(44), respectively.

Case II When $0.25 \le \alpha \le 0.5$, the equivalent parametric programming problem for model (32) is given as follows (34):

$$\begin{aligned}
&\text{Minimize } O_1 = \sum_i\sum_j y_i^j \times \left[\frac{(1-2\alpha)P_i^{1j}x_i^j + (2\alpha+(4\alpha-1)\eta_{l,i}^j)P_i^{2j}x_i^j}{1+(4\alpha-1)\eta_{l,i}^j}\right]\\
&\text{Minimize } O_2 = \sum_i\sum_j y_i^j \times \left[\frac{(1-2\alpha)R_i^{1j}x_i^j + (2\alpha+(4\alpha-1)\eta_{l,i}^j)R_i^{2j}x_i^j}{1+(4\alpha-1)\eta_{l,i}^j}\right]\\
&\text{Minimize } O_3 = \sum_i\sum_j y_i^j \times \left[\frac{(1-2\alpha)LD_i^{1j}x_i^j + (2\alpha+(4\alpha-1)\eta_{l,i}^j)LD_i^{2j}x_i^j}{1+(4\alpha-1)\eta_{l,i}^j}\right]\\
&\text{subject to}\\
&\sum_i\sum_j y_i^j \times x_i^j = D_{TD^j}\\
&\sum_i\sum_j y_i^j \times x_i^j \le D_{UL^i}\\
&\sum_i\sum_j y_i^j \times \left(D_{RV^i} \times x_i^j\right) \ge D_{PC}\\
&\sum_i\sum_j y_i^j \times \left(D_{QF^i} \times x_i^j\right) \le D_S\\
&\sum_i\sum_j y_i^j \times \left(D_{P_i^j} \times x_i^j\right) \le D_{B_i}\\
&x_i^j = \{y_i^j = 1 \text{ or } 0\}\\
&x_i^j \ge 0.
\end{aligned} \tag{34}$$

Case III When $0.5 \leq \alpha \leq 0.75$, the equivalent parametric programming problem for model (32) is given as follows (35):

$$
\begin{aligned}
&\text{Minimize } O_1 = \sum_i \sum_j y_i^j \times \left[\frac{(2\alpha - 1)P_i^{3j} x_i^j + (2(1-\alpha) + (3 - 4\alpha)\eta_{l,i}^j) P_i^{2j} x_i^j}{1 + (3 - 4\alpha)\eta_{l,i}^j} \right] \\
&\text{Minimize } O_2 = \sum_i \sum_j y_i^j \times \left[\frac{(2\alpha - 1)R_i^{3j} x_i^j + (2(1-\alpha) + (3 - 4\alpha)\eta_{l,i}^j) R_i^{2j} x_i^j}{1 + (3 - 4\alpha)\eta_{l,i}^j} \right] \\
&\text{Minimize } O_3 = \sum_i \sum_j y_i^j \times \left[\frac{(2\alpha - 1)LD_i^{3j} x_i^j + (2(1-\alpha) + (3 - 4\alpha)\eta_{l,i}^j) LD_i^{2j} x_i^j}{1 + (3 - 4\alpha)\eta_{l,i}^j} \right] \\
&\text{subject to} \\
&\qquad \sum_i \sum_j y_i^j \times x_i^j = D_{TD^j} \\
&\qquad \sum_i \sum_j y_i^j \times x_i^j \leq D_{UL^i} \\
&\qquad \sum_i \sum_j y_i^j \times \left(D_{RV^i} \times x_i^j\right) \geq D_{PC} \\
&\qquad \sum_i \sum_j y_i^j \times \left(D_{QF^i} \times x_i^j\right) \leq D_S \\
&\qquad \sum_i \sum_j y_i^j \times \left(D_{P_i^j} \times x_i^j\right) \leq D_{B_i} \\
&\qquad x_i^j = \{y_i^j = 1 \text{ or } 0\} \\
&\qquad x_i^j \geq 0.
\end{aligned} \tag{35}
$$

Case IV When $0.75 \leq \alpha \leq 1$, the equivalent parametric programming problem for model (32) is given as follows (36):

$$
\begin{aligned}
&\text{Minimize } O_1 = \sum_i \sum_j y_i^j \times \left[\frac{(2\alpha - 1 + (4\alpha - 3)\eta_{r,i}^j) P_i^{3j} x_i^j + 2(1-\alpha) P_i^{2j} x_i^j}{1 + (4\alpha - 3)\eta_{r,i}^j} \right] \\
&\text{Minimize } O_2 = \sum_i \sum_j y_i^j \times \left[\frac{(2\alpha - 1 + (4\alpha - 3)\eta_{r,i}^j) R_i^{3j} x_i^j + 2(1-\alpha) R_i^{2j} x_i^j}{1 + (4\alpha - 3)\eta_{r,i}^j} \right] \\
&\text{Minimize } O_3 = \sum_i \sum_j y_i^j \times \left[\frac{(2\alpha - 1 + (4\alpha - 3)\eta_{r,i}^j) LD_i^{3j} x_i^j + 2(1-\alpha) LD_i^{2j} x_i^j}{1 + (4\alpha - 3)\eta_{r,i}^j} \right] \\
&\text{subject to} \\
&\qquad \sum_i \sum_j y_i^j \times x_i^j = D_{TD^j} \\
&\qquad \sum_i \sum_j y_i^j \times x_i^j \leq D_{UL^i} \\
&\qquad \sum_i \sum_j y_i^j \times \left(D_{RV^i} \times x_i^j\right) \geq D_{PC} \\
&\qquad \sum_i \sum_j y_i^j \times \left(D_{QF^i} \times x_i^j\right) \leq D_S \\
&\qquad \sum_i \sum_j y_i^j \times \left(D_{P_i^j} \times x_i^j\right) \leq D_{B_i} \\
&\qquad x_i^j = \{y_i^j = 1 \text{ or } 0\} \\
&\qquad x_i^j \geq 0.
\end{aligned} \tag{36}
$$

where

$$
D_{TD^j} = \begin{cases}
\dfrac{(1 - 2\alpha_{i1}^j + (1 - 4\alpha_{i1}^j)\eta_{l,i}^j) TD^{j3} + 2\alpha_{i1}^j TD^{j2}}{1 + (1 - 4\alpha_{i1}^j)\eta_{l,i}^j}, & \text{if } 0 \leq \alpha_{i1}^j \leq 0.25, \\[2ex]
\dfrac{(1 - 2\alpha_{i1}^j) TD^{j3} + (2\alpha_{i1}^j + (4\alpha_{i1}^j - 1)\eta_{l,i}^j) TD^{j2}}{1 + (4\alpha_{i1}^j - 1)\eta_{r,i}^j}, & \text{if } 0.25 \leq \alpha_{i1}^j \leq 0.5, \\[2ex]
\dfrac{(2\alpha_{i1}^j - 1) TD^{j1} + (2(1 - \alpha_{i1}^j) + (3 - 4\alpha_{i1}^j)\eta_{r,i}^j) TD^{j2}}{1 + (3 - 4\alpha_{i1}^j)\eta_{r,i}^j}, & \text{if } 0.5 \leq \alpha_{i1}^j \leq 0.75, \\[2ex]
\dfrac{(2\alpha_{i1}^j - 1 + (4\alpha_{i1}^j - 3)\eta_{l,i}^j) TD^{j3} + 2(1 - \alpha_{i1}^j) TD^{j2}}{1 + (4\alpha_{i1}^j - 3)\eta_{l,i}^j}, & \text{if } 0.75 \leq \alpha_{i1}^j \leq 1.
\end{cases} \tag{37}
$$

$$
D_{UL^i} = \begin{cases}
\dfrac{(1 - 2\alpha_{i2}^j + (1 - 4\alpha_{i2}^j)\eta_{l,i}^j) UL^{i3} + 2\alpha_{i2}^j UL^{i2}}{1 + (1 - 4\alpha_{i2}^j)\eta_{l,i}^j}, & \text{if } 0 \leq \alpha_{i2}^j \leq 0.25, \\[2ex]
\dfrac{(1 - 2\alpha_{i2}^j) UL^{i3} + (2\alpha_{i2}^j + (4\alpha_{i2}^j - 1)\eta_{l,i}^j) UL^{i2}}{1 + (4\alpha_{i2}^j - 1)\eta_{r,i}^j}, & \text{if } 0.25 \leq \alpha_{i2}^j \leq 0.5, \\[2ex]
\dfrac{(2\alpha_{i2}^j - 1) UL^{i1} + (2(1 - \alpha_{i2}^j) + (3 - 4\alpha_{i2}^j)\eta_{r,i}^j) UL^{i2}}{1 + (3 - 4\alpha_{i2}^j)\eta_{r,i}^j}, & \text{if } 0.5 \leq \alpha_{i2}^j \leq 0.75, \\[2ex]
\dfrac{(2\alpha_{i2}^j - 1 + (4\alpha_{i2}^j - 3)\eta_{l,i}^j) UL^{i3} + 2(1 - \alpha_{i2}^j) UL^{i2}}{1 + (4\alpha_{i2}^j - 3)\eta_{l,i}^j}, & \text{if } 0.75 \leq \alpha_{i2}^j \leq 1.
\end{cases} \tag{38}
$$

$$
D_{RV^i} = \begin{cases}
\dfrac{(1 - 2\alpha_{i3}^j + (1 - 4\alpha_{i3}^j)\eta_{l,i}^j) RV^{i3} + 2\alpha_{i3}^j RV^{i2}}{1 + (1 - 4\alpha_{i3}^j)\eta_{l,i}^j}, & \text{if } 0 \leq \alpha_{i3}^j \leq 0.25, \\[2ex]
\dfrac{(1 - 2\alpha_{i3}^j) RV^{i3} + (2\alpha_{i3}^j + (4\alpha_{i3}^j - 1)\eta_{l,i}^j) RV^{i2}}{1 + (4\alpha_{i3}^j - 1)\eta_{r,i}^j}, & \text{if } 0.25 \leq \alpha_{i3}^j \leq 0.5, \\[2ex]
\dfrac{(2\alpha_{i3}^j - 1) RV^{i1} + (2(1 - \alpha_{i3}^j) + (3 - 4\alpha_{i3}^j)\eta_{r,i}^j) RV^{i2}}{1 + (3 - 4\alpha_{i3}^j)\eta_{r,i}^j}, & \text{if } 0.5 \leq \alpha_{i3}^j \leq 0.75, \\[2ex]
\dfrac{(2\alpha_{i3}^j - 1 + (4\alpha_{i3}^j - 3)\eta_{l,i}^j) RV^{i3} + 2(1 - \alpha_{i3}^j) RV^{i2}}{1 + (4\alpha_{i3}^j - 3)\eta_{l,i}^j}, & \text{if } 0.75 \leq \alpha_{i3}^j \leq 1.
\end{cases} \tag{39}
$$

$$
D_{PC} = \begin{cases}
\dfrac{(1 - 2\alpha_{i3}^j + (1 - 4\alpha_{i3}^j)\eta_{l,i}^j) PC^{3} + 2\alpha_{i3}^j PC^{2}}{1 + (1 - 4\alpha_{i3}^j)\eta_{l,i}^j}, & \text{if } 0 \leq \alpha_{i3}^j \leq 0.25, \\[2ex]
\dfrac{(1 - 2\alpha_{i3}^j) PC^{3} + (2\alpha_{i3}^j + (4\alpha_{i3}^j - 1)\eta_{l,i}^j) PC^{2}}{1 + (4\alpha_{i3}^j - 1)\eta_{r,i}^j}, & \text{if } 0.25 \leq \alpha_{i3}^j \leq 0.5, \\[2ex]
\dfrac{(2\alpha_{i3}^j - 1) PC^{1} + (2(1 - \alpha_{i3}^j) + (3 - 4\alpha_{i3}^j)\eta_{r,i}^j) PC^{2}}{1 + (3 - 4\alpha_{i3}^j)\eta_{r,i}^j}, & \text{if } 0.5 \leq \alpha_{i3}^j \leq 0.75, \\[2ex]
\dfrac{(2\alpha_{i3}^j - 1 + (4\alpha_{i3}^j - 3)\eta_{l,i}^j) PC^{3} + 2(1 - \alpha_{i3}^j) PC^{2}}{1 + (4\alpha_{i3}^j - 3)\eta_{l,i}^j}, & \text{if } 0.75 \leq \alpha_{i3}^j \leq 1.
\end{cases} \tag{40}
$$

$$
D_{QF^i} = \begin{cases}
\dfrac{(1 - 2\alpha_{i4}^j + (1 - 4\alpha_{i4}^j)\eta_{l,i}^j) QF^{i3} + 2\alpha_{i4}^j QF^{i2}}{1 + (1 - 4\alpha_{i4}^j)\eta_{l,i}^j}, & \text{if } 0 \leq \alpha_{i4}^j \leq 0.25, \\[2ex]
\dfrac{(1 - 2\alpha_{i4}^j) QF^{i3} + (2\alpha_{i4}^j + (4\alpha_{i4}^j - 1)\eta_{l,i}^j) QF^{i2}}{1 + (4\alpha_{i4}^j - 1)\eta_{r,i}^j}, & \text{if } 0.25 \leq \alpha_{i4}^j \leq 0.5, \\[2ex]
\dfrac{(2\alpha_{i4}^j - 1) QF^{i1} + (2(1 - \alpha_{i4}^j) + (3 - 4\alpha_{i4}^j)\eta_{r,i}^j) QF^{i2}}{1 + (3 - 4\alpha_{i4}^j)\eta_{r,i}^j}, & \text{if } 0.5 \leq \alpha_{i4}^j \leq 0.75, \\[2ex]
\dfrac{(2\alpha_{i4}^j - 1 + (4\alpha_{i4}^j - 3)\eta_{l,i}^j) QF^{i3} + 2(1 - \alpha_{i4}^j) QF^{i2}}{1 + (4\alpha_{i4}^j - 3)\eta_{l,i}^j}, & \text{if } 0.75 \leq \alpha_{i4}^j \leq 1.
\end{cases} \tag{41}
$$

$$D_S = \begin{cases} \dfrac{(1-2\alpha_{i4}^j + (1-4\alpha_{i4}^j)\eta_{l,i}^j)S^3 + 2\alpha_{i4}^j S^2}{1+(1-4\alpha_{i4}^j)\eta_{l,i}^j}, & \text{if } 0 \le \alpha_{i4}^j \le 0.25, \\ \dfrac{(1-2\alpha_{i4}^j)S^3 + (2\alpha_{i4}^j + (4\alpha_{i4}^j - 1)\eta_{l,i}^j)S^2}{1+(4\alpha_{i4}^j - 1)\eta_{r,i}^j}, & \text{if } 0.25 \le \alpha_{i4}^j \le 0.5, \\ \dfrac{(2\alpha_{i4}^j - 1)S^1 + (2(1-\alpha_{i4}^j) + (3-4\alpha_{i4}^j)\eta_{r,i}^j)S^2}{1+(3-4\alpha_{i4}^j)\eta_{r,i}^j}, & \text{if } 0.5 \le \alpha_{i4}^j \le 0.75, \\ \dfrac{(2\alpha_{i4}^j - 1 + (4\alpha_{i4}^j - 3)\eta_{l,i}^j)S^3 + 2(1-\alpha_{i4}^j)S^2}{1+(4\alpha_{i4}^j - 3)\eta_{l,i}^j}, & \text{if } 0.75 \le \alpha_{i4}^j \le 1. \end{cases} \tag{42}$$

$$D_{P_i^j} = \begin{cases} \dfrac{(1-2\alpha_{i5}^j + (1-4\alpha_{i5}^j)\eta_{l,i}^j)P_i^{j3} + 2\alpha_{i5}^j P_i^{j2}}{1+(1-4\alpha_{i5}^j)\eta_{l,i}^j}, & \text{if } 0 \le \alpha_{i5}^j \le 0.25, \\ \dfrac{(1-2\alpha_{i5}^j)P_i^{j3} + (2\alpha_{i5}^j + (4\alpha_{i5}^j - 1)\eta_{l,i}^j)P_i^{j2}}{1+(4\alpha_{i5}^j - 1)\eta_{r,i}^j}, & \text{if } 0.25 \le \alpha_{i5}^j \le 0.5, \\ \dfrac{(2\alpha_{i5}^j - 1)P_i^{j1} + (2(1-\alpha_{i5}^j) + (3-4\alpha_{i5}^j)\eta_{r,i}^j)P_i^{j2}}{1+(3-4\alpha_{i5}^j)\eta_{r,i}^j}, & \text{if } 0.5 \le \alpha_{i5}^j \le 0.75, \\ \dfrac{(2\alpha_{i5}^j - 1 + (4\alpha_{i5}^j - 3)\eta_{l,i}^j)P_i^{j3} + 2(1-\alpha_{i5}^j)P_i^{j2}}{1+(4\alpha_{i5}^j - 3)\eta_{l,i}^j}, & \text{if } 0.75 \le \alpha_{i5}^j \le 1. \end{cases} \tag{43}$$

$$D_{B_i} = \begin{cases} \dfrac{(1-2\alpha_{i5}^j + (1-4\alpha_{i5}^j)\eta_{l,i}^j)B_i^3 + 2\alpha_{i5}^j B_i^2}{1+(1-4\alpha_{i5}^j)\eta_{l,i}^j}, & \text{if } 0 \le \alpha_{i5}^j \le 0.25, \\ \dfrac{(1-2\alpha_{i5}^j)B_i^3 + (2\alpha_{i5}^j + (4\alpha_{i5}^j - 1)\eta_{l,i}^j)B_i^2}{1+(4\alpha_{i5}^j - 1)\eta_{r,i}^j}, & \text{if } 0.25 \le \alpha_{i5}^j \le 0.5, \\ \dfrac{(2\alpha_{i5}^j - 1)B_i^1 + (2(1-\alpha_{i5}^j) + (3-4\alpha_{i5}^j)\eta_{r,i}^j)B_i^2}{1+(3-4\alpha_{i5}^j)\eta_{r,i}^j}, & \text{if } 0.5 \le \alpha_{i5}^j \le 0.75, \\ \dfrac{(2\alpha_{i5}^j - 1 + (4\alpha_{i5}^j - 3)\eta_{l,i}^j)B_i^3 + 2(1-\alpha_{i5}^j)B_i^2}{1+(4\alpha_{i5}^j - 3)\eta_{l,i}^j}, & \text{if } 0.75 \le \alpha_{i5}^j \le 1. \end{cases} \tag{44}$$

Finally, the crisp version of multiobjective SSP (32) using generalized credibility method is summarized in models (33), (34), (35) and (36) depending on the range of α. One can select the desired range of α, and after that the corresponding crisp multiobjective SSP can be depicted for further solution.

3.2 Using Nearest Interval Approximation

Suppose that $\widetilde{(\cdot)}$ are mutually independent the type-2 triangular fuzzy variables depicted as $\widetilde{(\cdot)} = \left((\cdot)^1, (\cdot)^2, (\cdot)^3; \eta_{l,\cdot}, \eta_{r,\cdot}\right)$. We obtain the nearest interval approximations (credibilistic interval approximation, sub-section 2.2) of $\widetilde{(\cdot)}$. Let us assume that the nearest interval approximations of $\widetilde{(\cdot)}$ is represented by $\left[(\cdot)_L, (\cdot)_R\right]$. Using these nearest interval approximations, the multiobjective SSP (31) is transformed into the following interval programming problem (45):

$$\begin{aligned} &\text{Minimize } O_1 = \textstyle\sum_i \sum_j y_i^j \times \left(\left[P_{iL}^j, P_{iR}^j\right] \times x_i^j\right) \\ &\text{Minimize } O_2 = \textstyle\sum_i \sum_j y_i^j \times \left(\left[R_{iL}^j, R_{iR}^j\right] \times x_i^j\right) \\ &\text{Minimize } O_3 = \textstyle\sum_i \sum_j y_i^j \times \left(\left[LD_{iL}^j, LD_{iR}^j\right] \times x_i^j\right) \\ &\text{subject to} \\ &\textstyle\sum_i \sum_j y_i^j \times x_i^j = \left[TD_L^j, TD_R^j\right] \\ &\textstyle\sum_i \sum_j y_i^j \times x_i^j \le \left[UL_L^i, UL_R^i\right] \\ &\textstyle\sum_i \sum_j y_i^j \times \left(\left[RV_L^i, RV_R^i\right] \times x_i^j\right) \ge [PC_L, PC_R] \\ &\textstyle\sum_i \sum_j y_i^j \times \left([QF_{iL}, QF_{iR}] \times x_i^j\right) \le [S_L, S_R] \\ &\textstyle\sum_i \sum_j y_i^j \times \left(\left[P_{iL}^j, P_{iR}^j\right] \times x_i^j\right) \le [B_{iL}, B_{iR}] \\ &x_i^j = \{y_i^j = 1 \text{ or } 0\} \\ &x_i^j \ge 0. \end{aligned} \tag{45}$$

3.2.1 Deterministic Version

Firstly, we determine the deterministic version of the uncertain constraints using the concept of possibility degree of interval number [39] depicting a certain degree by which one interval is more substantial or smaller than the other. Here, we define the expressions for all the constraints of the multiobjective SSP (45) by achieving the possibility of satisfaction degrees or marginal evaluations of each interval parameters and can be given as follows:

$$C_{TD^j \le [TD^j_L, TD^j_R]} = \begin{cases} 1, & \text{if } \mathrm{TD^j} \le \mathrm{TD^j_L}, \\ \dfrac{TD^j_R - TD^j}{TD^j_R - TD^j_L}, & \text{if } \mathrm{TD^j_L} \le \mathrm{TD^j} \le \mathrm{TD^j_R}, \\ 0, & \text{if } \mathrm{TD^j} \ge \mathrm{TD^j_R} \end{cases}$$

$$C_{UL^i \le [UL^i_L, UL^i_R]} = \begin{cases} 1, & \text{if } \mathrm{UL^i} \le \mathrm{UL^i_L}, \\ \dfrac{UL^i_R - UL^i}{UL^i_R - UL^i_L}, & \text{if } \mathrm{UL^i_L} \le \mathrm{UL^i} \le \mathrm{UL^i_R}, \\ 0, & \text{if } \mathrm{UL^i} \ge \mathrm{UL^i_R} \end{cases}$$

$$C_{RV^i \le [RV^i_L, RV^i_R]} = \begin{cases} 1, & \text{if } \mathrm{RV^i} \le \mathrm{RV^i_L}, \\ \dfrac{RV^i_R - RV^i}{RV^i_R - RV^i_L}, & \text{if } \mathrm{RV^i_L} \le \mathrm{RV^i} \le \mathrm{RV^i_R}, \\ 0, & \text{if } \mathrm{RV^i} \ge \mathrm{RV^i_R} \end{cases}$$

$$C_{PC \ge [PC_L, PC_R]} = \begin{cases} 0, & \text{if } \mathrm{PC} \le \mathrm{PC_L}, \\ \dfrac{PC - PC_L}{PC_R - PC_L}, & \text{if } \mathrm{PC_L} \le \mathrm{PC} \le \mathrm{PC_R}, \\ 1, & \text{if } \mathrm{PC} \ge \mathrm{PC_R} \end{cases}$$

$$C_{QF_i \ge [QF_{iL}, QF_{iR}]} = \begin{cases} 0, & \text{if } \mathrm{QF_i} \le \mathrm{QF_{iL}}, \\ \dfrac{QF_i - QF_{iL}}{QF_{iR} - QF_{iL}}, & \text{if } \mathrm{QF_{iL}} \le \mathrm{QF_i} \le \mathrm{QF_{iR}}, \\ 1, & \text{if } \mathrm{QF_i} \ge \mathrm{QF_{iR}} \end{cases}$$

$$C_{S \le [S_L, S_R]} = \begin{cases} 1, & \text{if } \mathrm{S} \le \mathrm{S_L}, \\ \dfrac{S_R - S}{S_R - S_L}, & \text{if } \mathrm{S_L} \le \mathrm{S} \le \mathrm{S_R}, \\ 0, & \text{if } \mathrm{S} \ge \mathrm{S_R} \end{cases}$$

$$C_{P^j_i \ge [P^j_{iL}, P^j_{iR}]} = \begin{cases} 0, & \text{if } \mathrm{P^j_i} \le \mathrm{P^j_{iL}}, \\ \dfrac{P^j_i - P^j_{iL}}{P^j_{iR} - P^j_{iL}}, & \text{if } \mathrm{P^j_{iL}} \le \mathrm{P^j_i} \le \mathrm{P^j_{iR}}, \\ 1, & \text{if } \mathrm{P^j_i} \ge \mathrm{P^j_{iR}} \end{cases}$$

$$C_{B_i \le [B_{iL}, B_{iR}]} = \begin{cases} 1, & \text{if } \mathrm{B_i} \le \mathrm{B_{iL}}, \\ \dfrac{B_{iR} - B_i}{B_{iR} - B_{iL}}, & \text{if } \mathrm{B_{iL}} \le \mathrm{B_i} \le \mathrm{B_{iR}}, \\ 0, & \text{if } \mathrm{B_i} \ge \mathrm{B_{iR}} \end{cases}$$

If all the constraints are permitted to be satisfied with some specified possibility level between 0 and 1, such as, $C_{TD^j \le [TD^j_L, TD^j_R]} \ge \alpha^j_{i1}$, $C_{UL^i \le [UL^i_L, UL^i_R]} \ge \alpha^j_{i2}$, $C_{RV^i \le [RV^i_L, RV^i_R]} \ge \alpha^j_{i3}$, $C_{PC \ge [PC_L, PC_R]} \ge \alpha^j_{i3}$, $C_{QF_i \ge [QF_{iL}, QF_{iR}]} \ge \alpha^j_{i4}$, $C_{S \le [S_L, S_R]} \ge \alpha^j_{i4}$, $C_{P^j_i \ge [P^j_{iL}, P^j_{iR}]} \ge \alpha^j_{i5}$ and $C_{B_i \le [B_{iL}, B_{iR}]} \ge \alpha^j_{i5}$, then the equivalent deterministic inequalities of the respective constraints are depicted as follows:

$$TD^j \le TD^j_R - \alpha^j_{i1}\left[TD^j_R - TD^j_L\right], \forall\, i, j. \tag{46}$$

$$UL^i \le UL^i_R - \alpha^j_{i2}\left[UL^i_R - UL^i_L\right], \forall\, i, j. \tag{47}$$

$$RV^i \le RV^i_R - \alpha^j_{i3}\left[RV^i_R - RV^i_L\right], \forall\, i, j. \tag{48}$$

$$PC \ge PC_L + \alpha^j_{i3}[PC_R - PC_L], \forall\, i, j. \tag{49}$$

$$QF_i \ge QF_R + \alpha^j_{i4}[QF_R - QF_L], \forall\, i, j. \tag{50}$$

$$S \le S_R - \alpha^j_{i4}[S_R - S_L], \forall\, i, j. \tag{51}$$

$$P^j_i \ge P^j_{iR} + \alpha^j_{i5}\left[P^j_{iR} - P^j_{iL}\right], \forall\, i, j. \tag{52}$$

$$B_i \le B_{iR} - \alpha^j_{i5}[B_{iR} - B_{iL}], \forall\, i, j. \tag{53}$$

We have transformed each objective function into two different sub-objective while dealing with the interval parameters. A lower/minimum value of each objective is calculated by $\underline{O_1}, \underline{O_2}$ and $\underline{O_3}$ whereas the upper/maximum values are determined by $\overline{O_1}, \overline{O_2}$ and $\overline{O_3}$, respectively. We have solved for the following individual objective function under the constraints (46)–(53).

$$\underline{O_1} = \mathrm{Min}_{P^j_{iL} \le P^j_i \le P^j_{iR}} \left[\mathrm{Min} \sum_i \sum_j y^j_i \times \left(P^j_i \times x^j_i\right)\right],$$

$$\overline{O_1} = \mathrm{Max}_{P^j_{iL} \le P^j_i \le P^j_{iR}} \left[\mathrm{Min} \sum_i \sum_j y^j_i \times \left(P^j_i \times x^j_i\right)\right]$$

$$\underline{O_2} = \mathrm{Min}_{R^j_{iL} \le R^j_i \le R^j_{iR}} \left[\mathrm{Min} \sum_i \sum_j y^j_i \times \left(R^j_i \times x^j_i\right)\right],$$

$$\overline{O_2} = \mathrm{Max}_{R^j_{iL} \le R^j_i \le R^j_{iR}} \left[\mathrm{Min} \sum_i \sum_j y^j_i \times \left(R^j_i \times x^j_i\right)\right]$$

$$\underline{O_3} = \mathrm{Min}_{LD^j_{iL} \le LD^j_i \le LD^j_{iR}} \left[\mathrm{Min} \sum_i \sum_j y^j_i \times \left(LD^j_i \times x^j_i\right)\right],$$

$$\overline{O_3} = \mathrm{Max}_{LD^j_{iL} \le LD^j_i \le LD^j_{iR}} \left[\mathrm{Min} \sum_i \sum_j y^j_i \times \left(LD^j_i \times x^j_i\right)\right]$$

Thus the equivalent deterministic interval multiobjective SSP (45) can be stated as follows (54):

$$\begin{gathered}
\underline{O_1} = \mathrm{Min}_{P_{iL}^j \le P_i^j \le P_{iR}^j}\left[\mathrm{Min}\sum_i\sum_j y_i^j \times \left(P_i^j \times x_i^j\right)\right] \\
\overline{O_1} = \mathrm{Max}_{P_{iL}^j \le P_i^j \le P_{iR}^j}\left[\mathrm{Min}\sum_i\sum_j y_i^j \times \left(P_i^j \times x_i^j\right)\right] \\
\underline{O_2} = \mathrm{Min}_{R_{iL}^j \le R_i^j \le R_{iR}^j}\left[\mathrm{Min}\sum_i\sum_j y_i^j \times \left(R_i^j \times x_i^j\right)\right] \\
\overline{O_2} = \mathrm{Max}_{R_{iL}^j \le R_i^j \le R_{iR}^j}\left[\mathrm{Min}\sum_i\sum_j y_i^j \times \left(R_i^j \times x_i^j\right)\right] \\
\underline{O_3} = \mathrm{Min}_{LD_{iL}^j \le LD_i^j \le LD_{iR}^j}\left[\mathrm{Min}\sum_i\sum_j y_i^j \times \left(LD_i^j \times x_i^j\right)\right] \\
\overline{O_3} = \mathrm{Max}_{LD_{iL}^j \le LD_i^j \le LD_{iR}^j}\left[\mathrm{Min}\sum_i\sum_j y_i^j \times \left(LD_i^j \times x_i^j\right)\right] \\
\text{subject to} \\
\text{constraints } (46)-(53) \\
x_i^j = \left\{y_i^j = 1 \text{ or } 0\right\} \\
x_i^j \ge 0.
\end{gathered} \tag{54}$$

Hence the obtained multiobjective SSP (54) can be solved to determine the optimal compromise solution for each objective function.

4 Proposed Interactive Neutrosophic Programming Approach

Many multiobjective optimization techniques are popular among researchers. Based on the fuzzy set, different fuzzy optimization method came into existence. In the fuzzy programming approach, the marginal evaluation of each objective function is depicted by only the membership functions and can be achieved by maximizing it. The extension of the fuzzy optimization method is presented by introducing intuitionistic fuzzy optimization techniques. It is comparatively more advanced than the fuzzy technique because the marginal evaluation of each objective function is depicted by the membership and non-membership functions, which can be achieved by maximizing the membership and minimizing the non-membership functions, respectively. The real-life complexity most often creates the indeterminacy situation or neutral thoughts while making optimal decisions. Apart from the acceptance and rejection degrees in the decision-making process, the indeterminacy degree also has much importance. Thus to cover the neutral thoughts or indeterminacy degree of the element into the feasible solution set, Smarandache [29] investigated a neutrosophic set. The name "*neutrosophic*" is the advance combination of two explicit terms, namely; "*neutre*" extracted from French means, neutral, and "*sophia*" adopted from Greek means, skill/wisdom, that unanimously provide the definition "*knowledge of neutral thoughts*" (see Smarandache [29], Ahmad and Adhami [3]). The NS considers three sorts of membership functions, such as truth (degree of belongingness), indeterminacy (degree of belongingness up to some extent), and a falsity (degree of non-belongingness) degrees into the feasible solution set. The idea of independent, neutral thoughts differs the NS with all the uncertain decision sets such as FS and IFS. The updated literature work solely highlights that many practitioners or researchers have taken the deep interest in the neutrosophic research field (see, Ahmad and Adhami [4], Ahmad et al. [5], Ahmad et al. [6]). The NS research domain would get exposure in the future and assist in dealing with indeterminacy or neutral thoughts in the decision-making process. This study also fetches the novel ideas of neutrosophic optimization techniques based on the NS. A novel interactive neutrosophic programming approach is developed to solve the multiobjective SSP under type-2 fuzzy parameters. The marginal evaluation of each objective function is quantified by the truth, indeterminacy, and falsity membership functions under the neutrosophic decision set. Thus the NS plays a vital role while optimizing the multiobjective optimization problems by incorporating, executing, and implementing the neutral thoughts. Consider the general formulation of multiobjective programming problem (MOPP) with k objectives as follows:

$$\begin{aligned}
&\text{Minimize } (\mathrm{O_1(x), O_2(x), \ldots, O_k(x)}) \\
&\text{s.t.} \\
&H(x) \le 0, \; x \ge 0
\end{aligned} \tag{55}$$

where $O_k(x)$ is the k^{th} objective functions and; $H(x)$ and x are the real valued function and a set of decision variables.

Bellman and Zadeh [8] first propounded the idea of a fuzzy decision set. After that, it is widely adopted by many researchers. The fuzzy decision concept comprises fuzzy decision (D), fuzzy goal (G), and fuzzy constraints (C), respectively. Here, we recall the most extensively used fuzzy decision set with the aid of following mathematical expressions:

$$D = O \cap C$$

Consequently, we also depict the neutrosophic decision set D_N, which contemplate over neutrosophic objectives and constraints as follows: Consequently, we also depict the neutrosophic decision set D_N, which contemplate over neutrosophic objectives and constraints as follows:

$$\begin{aligned}
D_N &= (\cap_{k=1}^{K} O_k)(\cap_{i=1}^{I} C_i) \\
&= (x,\, \mu_D(x),\, \lambda_D(x),\, \nu_D(x))
\end{aligned}$$

where

$$\mu_D(x) = \min\left\{ \begin{array}{l} \mu_{O_1}(x), \mu_{O_2}(x), \ldots, \mu_{O_k}(x) \\ \mu_{C_1}(x), \mu_{C_2}(x), \ldots, \mu_{C_i}(x) \end{array} \right\} \forall\ x \in X$$

$$\lambda_D(x) = \max\left\{ \begin{array}{l} \lambda_{O_1}(x), \lambda_{O_2}(x), \ldots, \lambda_{O_k}(x) \\ \lambda_{C_1}(x), \lambda_{C_2}(x), \ldots, \lambda_{C_i}(x) \end{array} \right\} \forall\ x \in X$$

$$\nu_D(x) = \max\left\{ \begin{array}{l} \nu_{O_1}(x), \nu_{O_2}(x), \ldots, \nu_{O_k}(x) \\ \nu_{C_1}(x), \nu_{C_2}(x), \ldots, \nu_{C_i}(x) \end{array} \right\} \forall\ x \in X$$

where $\mu_D(x), \lambda_D(x)$ and $\nu_D(x)$ are the truth, indeterminacy and a falsity membership functions of neutrosophic decision set D_N , respectively.

In order to depict the different membership functions for MOPP (55), the minimum and maximum values of each objective functions have been represented by L_k and U_k and; can be obtained as follows:

$$U_k = \max\left[\mathrm{O_k(x)}\right] \text{ and } \mathrm{L_k} = \min\left[\mathrm{O_k(x)}\right] \ \ \forall\, \mathrm{k} = 1, 2, 3, \ldots, \mathrm{K}. \tag{56}$$

The bounds for kth objective function under the neutrosophic environment can be obtained as follows:

$$U_k^\mu = U_k, \quad L_k^\mu = L_k$$
$$U_k^\lambda = L_k^\mu + s_k, \quad L_k^\lambda = L_k^\mu$$
$$U_k^\nu = U_k^\mu, \quad L_k^\nu = L_k^\mu + t_k$$

where s_k and $t_k \in (0, 1)$ are pre-determined real numbers prescribed by decision-makers.

The linear-type truth $\mu_k(O_k(x))$, indeterminacy $\lambda_k(O_k(x))$ and a falsity $\nu_k(O_k(x))$ membership functions under neutrosophic environment can be furnished as follows:

$$\mu_k(O_k(x)) = \begin{cases} 1 & \text{if } O_k(x) \le L_k^\mu \\ \dfrac{U_k^\mu - O_k(x)}{U_k^\mu - L_k^\mu} & \text{if } L_k^\mu \le O_k(x) \le U_k^\mu \\ 0 & \text{if } O_k(x) \ge U_k^\mu \end{cases} \tag{57}$$

$$\lambda_k(O_k(x)) = \begin{cases} 1 & \text{if } O_k(x) \le L_k^\lambda \\ \dfrac{U_k^\lambda - O_k(x)}{U_k^\lambda - L_k^\lambda} & \text{if } L_k^\lambda \le O_k(x) \le U_k^\lambda \\ 0 & \text{if } O_k(x) \ge U_k^\lambda \end{cases} \tag{58}$$

$$\nu_k(O_k(x)) = \begin{cases} 0 & \text{if } O_k(x) \le L_k^\nu \\ \dfrac{O_k(x) - L_k^\nu}{U_k^\nu - L_k^\nu} & \text{if } L_k^\nu \le O_k(x) \le U_k^\nu \\ 1 & \text{if } O_k(x) \ge U_k^\nu \end{cases} \tag{59}$$

In the above case, $L_k \ne U_k$ for all k objective function. If for any membership $L_k = U_k$, then the value of these membership will be equal to 1.

Introducing the idea of [8], we maximize the overall achievement function to reach the optimal solution of each objectives. The mathematical expression for achievement function is defined as follows:

$$\begin{array}{l} \text{Max } \min_{k=1,2,3,\ldots,K}\ \mu_k(O_k(x)) \\ \text{Min } \max_{k=1,2,3,\ldots,K}\ \lambda_k(O_k(x)) \\ \text{Min } \max_{k=1,2,3,\ldots,K}\ \nu_k(O_k(x)) \\ \qquad\qquad \text{subject to} \\ \quad \text{all the constraints of}\,(55) \end{array} \tag{60}$$

Also, assume that $\mu_k(O_k(x)) \ge \delta$, $\lambda_k(O_k(x)) \le \beta$ and $\nu_k(O_k(x)) \le \gamma$, for all k.

With the aid of auxiliary parameters δ, β and γ, the problem (60) can be transformed into the following problem (61):

$$(INPA) \qquad \begin{array}{c} \text{Max } \psi(x) = \theta(\delta - \beta - \gamma) + (1 - \theta) \\ \sum_{k=1}^{K} (\mu_k(O_k(x)) - \lambda_k(O_k(x)) - \nu_k(O_k(x))) \\ \text{subject to} \\ \mu_k(O_k(x)) \ge \delta, \\ \lambda_k(O_k(x)) \le \beta, \\ \nu_k(O_k(x)) \le \gamma, \\ \delta \ge \beta,\ 0 \le \delta + \beta + \gamma \le 3, \\ \delta, \beta, \gamma \in [0, 1] \\ \text{all the constraints of}\,(55) \end{array} \tag{61}$$

where θ is the compensation co-efficient between the overall satisfaction level and the sum of individual marginal evaluation of each objective function in neutrosophic environment. Thus the development of proposed INPA (61) has a new achievement function which is represented by a convex combination of differences among the bounds for truth, indeterminacy and falsity degrees of objective function $(\delta - \beta - \gamma)$, and the sum of differences among these achievement degrees $(\mu_k(O_k(x)) - \lambda_k(O_k(x)) - \nu_k(O_k(x)))$ to make sure generating an established balanced compromise solution.

Definition 5 A vector $x^* \in X$ is said to be an optimal solution to proposed INPA (61) or an efficient solution to the crisp MOPP (55) if and only if there does not exist any $x \in X$ such that, $\mu_k(x) \ge \mu_k(x^*)$, $\lambda_k(x) \le \lambda_k(x^*)$ and $\nu_k(x) \le \nu_k(x^*)$, $\forall\ k = 1, 2, \ldots, K$.

Theorem 3 *A unique optimal solution of proposed INPA (61) is also an efficient solution to the crisp MOPP (55).*

Proof Consider that x^* be a unique optimal solution of proposed INPA (61) which is not an efficient solution to crisp MOPP (55). It means that there must be an efficient solution, say x^{**}, for the crisp MOPP (55) so that we can have: $\mu_k(x^{**}) \ge \mu_k(x^*)$, $\lambda_k(x^{**}) \le \lambda_k(x^*)$ and

$\nu_k(x^{**}) \leq \nu_k(x^*)$; $\forall\ k = 1, 2, \ldots, K$. Thus for the overall satisfaction level of each objective functions in x^* and x^{**} solutions, we would have $(\delta - \beta - \gamma)(x^{**}) \geq (\delta - \beta - \gamma)(x^*)$, and concerning the related objective values we would have the following inequalities:

$$\begin{aligned}\psi(x^*) &= \theta(\delta - \beta - \gamma)(x^*) \\ &\quad + (1-\theta)\left[\sum_{k=1}^{K}(\mu_k(O_k(x^*)) \right.\\ &\quad \left. - \lambda_k(O_k(x^*)) - \nu_k(O_k(x^*)))\right] \\ &< \theta(\delta - \beta - \gamma)(x^{**}) \\ &\quad + (1-\theta)\left[\sum_{k \neq t}(\mu_k(O_k(x^{**})) \right.\\ &\quad \left. - \lambda_k(O_k(x^{**})) - \nu_k(O_k(x^{**})))\right] \\ &= \psi(x^{**}).\end{aligned}$$

Hence, we have arrived at a contradiction that x^* is not a unique optimal solution of proposed INPA (61). This completes the proof of Theorem 3. □

5 Computational Study

Consider an automobile company orders the number of different parts to various suppliers. The outer purchases of the parts approximately in turn into 76% of the total cost, which is quite large. The available resources for manufacturing purposes are limited. Therefore, to select the suppliers based on the different purchasing behavior, several experts are assigned. The experts have designed the selection criteria based on the certain ordered quality with its limitations. The experts have suggested the various parameters as type-2 triangular fuzzy numbers because of the existence of primary and secondary possibility degrees of each element into the feasible decision set. The proposed multiobjective SSP is implemented with the three different objectives comprising the minimization of total ordering cost, rejection rate, and delivery time of the items under a set of available resources. The crisp multiobjective SSP is written in AMPL, and solution results are obtained using Knitro 10.3.0 through NEOS server version 5.0, accessed allowed by Wisconsin Institutes for Discovery, University of Wisconsin, Madison See, Dolan [9], Server [28].

5.1 Solution Results Using Chance-Constrained Programming Method

We have represented the chance-constrained programming problem for multiobjective SSP (32). For each objective function and constraints, we have defined the predetermined credibility levels such as $\alpha = \alpha_{i1} = \alpha_{i2} = \alpha_{i3} = \alpha_{i4} = \alpha_{i5} = 0.9,\ \forall\ i = 1, 2, \cdot, 5,\ j = 1, 2, 3$. Table 2 depicts the type-2 triangular fuzzy parameters for the proposed mulltiobjective SSP.

With the aid of model (36), the corresponding crisp form of the SSP can be given as follows (62):

$$\begin{aligned}&\text{Minimize } O_1 = \textstyle\sum_i \sum_j y_i^j \\ &\quad \times \left[\frac{(2\alpha - 1 + (4\alpha - 3)\eta_{r,i}^j)P_i^{3j}x_i^j + 2(1-\alpha)P_i^{2j}x_i^j}{1 + (4\alpha - 3)\eta_{r,i}^j}\right] \\ &\text{Minimize } O_2 = \textstyle\sum_i \sum_j y_i^j \\ &\quad \times \left[\frac{(2\alpha - 1 + (4\alpha - 3)\eta_{r,i}^j)R_i^{3j}x_i^j + 2(1-\alpha)R_i^{2j}x_i^j}{1 + (4\alpha - 3)\eta_{r,i}^j}\right] \\ &\text{Minimize } O_3 = \textstyle\sum_i \sum_j y_i^j \\ &\quad \times \left[\frac{(2\alpha - 1 + (4\alpha - 3)\eta_{r,i}^j)LD_i^{3j}x_i^j + 2(1-\alpha)LD_i^{2j}x_i^j}{1 + (4\alpha - 3)\eta_{r,i}^j}\right] \\ &\text{subject to} \\ &\qquad \textstyle\sum_i \sum_j y_i^j \times x_i^j = D_{TD^j} \\ &\qquad \textstyle\sum_i \sum_j y_i^j \times x_i^j \leq D_{UL^i} \\ &\qquad \textstyle\sum_i \sum_j y_i^j \times \left(D_{RV^i} \times x_i^j\right) \geq D_{PC} \\ &\qquad \textstyle\sum_i \sum_j y_i^j \times \left(D_{QF^i} \times x_i^j\right) \leq D_S \\ &\qquad \textstyle\sum_i \sum_j y_i^j \times \left(D_{P_i^j} \times x_i^j\right) \leq D_{B_i} \\ &\qquad x_i^j = \{y_i^j = 1 \text{ or } 0\} \\ &\qquad x_i^j \geq 0.\end{aligned} \tag{62}$$

where $D_{TD^j}, D_{UL^i}, D_{RV^i}, D_{PC}, D_{QF^i}, D_S, D_{P_i^j}, D_{B_i}\ \forall\ i\ \&\ j$ are calculated using Eqs. (37)–(44), respectively.

On solving the problem (62) using proposed INPA, we get the optimal objective values as $O_1 = 62138$, $O_2 = 436$ and $O_3 = 784$ with the overall satisfaction level $\psi(x) = 0.7216$. The total computational time was 1.3642 sec.

5.2 Solution Results Using Nearest Interval Approximation

The credibilistic nearest interval approximation of the type-2 fuzzy parameters are determined with the help of Eqs. (19) and (20). All the equivalent data in the interval form are summarized in Table 3.

Suppose that the satisfaction level with the possible degree of each parameter in the constraints is 0.85. Thus the corresponding crisp version of all the constraints is determined with the help of Eqs. (46)–(53). On applying the proposed INPA, the compromise solution of the multiobjective SSP (54) is obtained as follows:

Table 2 Supplier source data type-2 fuzzy parameters

Parameters	No. of items (j)	No. of suppliers (i)				
		1	2	3	4	5
$\widetilde{P}_i^j$(\$/units)	1	(12,15,18; 0.54,0.61)	(14,16,18; 0.32,0.65)	(16,18,20; 0.65,0.47)	(28,30,32; 0.74,0.98)	(36,40,44; 0.64,0.85)
	2	(18,20,22; 0.52,0.75)	(22,25,28; 0.54,0.86)	(25,27,29; 0.75,0.68)	(16,18,22; 0.23,0.67)	(27,29,31; 0.24,0.26)
	3	(28,30,32; 0.62,0.81)	(36,40,44; 0.32,0.52)	(40,43,46; 0.41,0.16)	(10,12,14; 0.45,0.64)	(12,14,16; 0.75,0.68)
$\widetilde{R}_i^j$(%)	1	(0.12,0.15,0.18; 0.23,0.56)	(0.14,0.16,0.18; 0.32,0.85)	(0.16,0.18,0.20; 0.35,0.65)	(0.28,0.30,0.32; 0.54,0.87)	(0.36,0.40,0.44; 0.65,0.95)
	2	(0.18,0.20,0.22; 0.64,0.83)	(0.22,0.25,0.28; 0.95,0.24)	(0.25,0.27,0.29; 0.62,0.57)	(0.36,0.68,0.10; 0.65,0.48)	(0.27,0.49,0.11; 0.42,0.36)
	3	(0.28,0.30,0.32; 0.43,0.57)	(0.36,0.40,0.44; 0.64,0.92)	(0.40,0.43,0.46; 0.64,0.63)	(0.10,0.12,0.14; 0.85,0.94)	(0.12,0.14,0.16; 0.16,0.65)
$\widetilde{UL}_i^j$(units)	1	(10,12,14; 0.45,0.64)	(25,27,29; 0.75,0.68)	(40,43,46; 0.41,0.16)	(36,40,44; 0.64,0.85)	(36,40,44; 0.32,0.52)
	2	(12,14,16; 0.75,0.68)	(18,20,22; 0.52,0.75)	(36,40,44; 0.32,0.52)	(28,30,32; 0.62,0.81)	(14,16,18; 0.32,0.65)
	3	(28,30,32; 0.62,0.81)	(22,25,28; 0.54,0.86)	(25,27,29; 0.75,0.68)	(18,20,22; 0.52,0.75)	(12,15,18; 0.54,0.61)
$\widetilde{LD}_i^j$(%)	1	(0.61,0.54,0.21; 0.65,0.61)	(0.21,0.35,0.34; 0.62,0.61)	(0.36,0.40,0.44; 0.64,0.92)	(0.40,0.43,0.46; 0.64,0.63)	(0.22,0.25,0.28; 0.95,0.24)
	2	(0.27,0.49,0.11; 0.42,0.36)	(0.21,0.12,0.14; 0.39,0.37)	(0.28,0.30,0.32; 0.43,0.57)	(0.12,0.14,0.16; 0.16,0.65)	(0.14,0.16,0.18; 0.32,0.85)
	3	(0.12,0.24,0.52; 0.31,0.36)	(0.11,0.31,0.45; 0.65,0.85)	(0.21,0.31,0.36; 0.65,0.45)	(0.34,0.61,0.42; 0.61,0.86)	(0.21,0.63,0.45; 0.65,0.89)
$\widetilde{RV}_i$		(18,20,22; 0.21,0.65)	(22,25,28; 0.61,0.86)	(25,27,29; 0.75,0.64)	(26,28,29; 0.81,0.67)	(37,39,41; 0.64,0.83)
$\widetilde{QF}_i$		(40,45,50; 0.42,0.64)	(45,50,55; 0.64,0.86)	(65,70,75; 0.64,0.82)	(12,15,18; 0.64,0.46)	(14,16,18; 0.64,0.76)
$\widetilde{B}_i$(\$)		(56,52,34; 0.64,0.83)	(83,86,89; 0.64,0.46)	(78,84,96; 0.67,0.48)	(46,52,56; 0.64,0.98)	(64,68,74; 0.94,0.86)

	No. of items (j)		
	1	2	3
$\widetilde{TD}^j$(units)	(125, 165, 195; 0.60,0.70)	(215, 235, 245; 0.35,0.75)	(320, 345, 385; 0.45,0.85)
$\widetilde{PC}$	(45230, 57840, 61250; 0.6, 0.8)		
$\widetilde{S}$	(944750, 965840, 985470; 0.4, 0.7)		

$\underline{O}_1 = 59021$, $\overline{O}_1 = 82513$, $\underline{O}_2 = 389$, $\overline{O}_2 = 552$ and $\underline{O}_3 = 693$, $\overline{O}_3 = 936$ with the overall satisfaction level $\psi(x) = 0.6909$. The total computational time was 0.9651 sec.

5.3 Discussions

The two defuzzified technique for the type-2 fuzzy parameters inherently focuses on the different aspects of decision-makers' choices. The CV-based reduction method and nearest interval approximation technique are used to obtain the equivalent type-1 fuzzy parameters (or fuzzy) of the type-2 fuzzy parameters at an α-value. Since the defuzzified values are different, the outcomes are also conflicting. For the CV-based reduction method, all the objective values fall within the optimal range of the solution results obtained by the nearest interval approximation techniques. So, it is not worthy of commenting on the performances of the defuzzification techniques. The primary reason may be the different defuzzified values of the type-2 triangular fuzzy parameters, which yield different objective values. Further, the various solution results can be generated by tuning the values of α. Implementation of the proposed INPA can also assist the decision-makers to select the best optimal outcomes of the multiobjective SSP.

After getting the global solution result using the proposed INPA, there is still an ample opportunity to obtain more specific and comprehensive outcomes by tuning additional parameters (α) (vagueness degree) present in vague constraints. Table 4 illustrates an overall satisfaction level solution for single value of vagueness degree at $\alpha = 0.9$. Hence it would be worth useful for managers to record the influence of parameter α with the overall satisfaction level $(\delta - \beta - \gamma)$ which is graphically represented in Figure 1. For linear-type membership functions, the parameter α is tuned for different values. As Table 4 and Figure 1 reveal that when parameter α increases, the overall

Table 3 Supplier source data in interval form

Parameters	No. of items (j)	No. of suppliers (i)				
		1	2	3	4	5
$\widetilde{P}_i^j$(\$/units)	1	(12, 61)	(14, 65)	(16, 47)	(28, 98)	(36, 85)
	2	(18, 75)	(22, 86)	(25, 68)	(16, 67)	(27, 56)
	3	(28, 81)	(36, 52)	(40, 86)	(10, 64)	(12, 68)
$\widetilde{R}_i^j$(%)	1	(0.12, 0.56)	(0.14, 0.85)	(0.16, 0.65)	(0.28, 0.87)	(0.36, 0.95)
	2	(0.18, 0.83)	(0.22, 0.64)	(0.25, 0.57)	(0.36, 0.58)	(0.27, 0.66)
	3	(0.28, 0.57)	(0.36, 0.92)	(0.40, 0.63)	(0.10, 0.94)	(0.12, 0.65)
$\widetilde{UL}_i^j$(units)	1	(10, 64)	(25, 68)	(40, 16)	(36, 85)	(36, 52)
	2	(12, 68)	(18, 75)	(36, 52)	(28, 81)	(14, 65)
	3	(28, 81)	(22, 86)	(25, 68)	(18, 75)	(12, 61)
$\widetilde{LD}_i^j$(%)	1	(0.61, 0.86)	(0.62, 0.78)	(0.36, 0.92)	(0.40, 0.63)	(0.22, 0.78)
	2	(0.27, 0.36)	(0.21, 0.37)	(0.28, 0.57)	(0.12, 0.65)	(0.14, 0.85)
	3	(0.12, 0.36)	(0.11, 0.85)	(0.21, 0.45)	(0.61, 0.86)	(0.65, 0.89)
$\widetilde{RV}_i$		(16, 58)	(60, 78)	(28, 62)	(32, 68)	(36, 86)
$\widetilde{QF}_i$		(26, 48)	(43, 57)	(44, 65)	(45, 68)	(48, 26)
$\widetilde{B}_i$(\$)		(62, 76)	(54, 86)	(24, 56)	(57, 81)	(73, 92)

	No. of items (j)		
	1	2	3
$\widetilde{TD}^j$(units)	(120, 180)	(210, 260)	(300, 340)
$\widetilde{PC}$	(47840, 49562)		
$\widetilde{S}$	(925647, 945681)		

Table 4 Overall satisfaction level $(\delta-\beta-\gamma)$ achieved using INPA

Degree of vagueness	Compensation co-efficient				
α	$\theta=0.1$	$\theta=0.3$	$\theta=0.5$	$\theta=0.7$	$\theta=0.9$
0.1	0.8289	0.8277	0.8268	0.8261	0.8156
0.2	0.8187	0.8179	0.8171	0.8167	0.8156
0.3	0.8121	0.8113	0.8198	0.8187	0.8173
0.4	0.8076	0.8064	0.8059	0.8056	0.8049
0.5	0.8027	0.8022	0.8013	0.8005	0.7986
0.6	0.7931	0.7919	0.7902	0.7989	0.7971
0.7	0.7822	0.7809	0.7896	0.7881	0.7873
0.8	0.7788	0.7781	0.7776	0.7771	0.7767
0.9	0.7667	0.7653	0.7641	0.7635	0.7622
1	0.7543	0.7534	0.7531	0.7524	0.7518

satisfaction degree of managers decreases. It may be concluded that the nearer the α values reaches to 0, the more likely the problem be to a crisp SSP model, and the overall degree of satisfaction will always 1. This same behavior is noticed for different compensation co-efficient θ values, the only difference being the initial point for the minimum vagueness degrees. For $\alpha=0.9$, $\theta=0.1$, the satisfaction level is found to be 0.8289 and reaches towards its worst at $\alpha=0.9$, $\theta=0.9$ which is 0.7518. As discussed before, a higher overall satisfaction level $(\delta-\beta-\gamma)$ can be attained with higher compensation co-efficient θ values. The downward trend is shown for the parameter α means that an increment in these values will lead to the reduction in overall satisfaction level $(\delta-\beta-\gamma)$ and vice-versa. To determine the best possible outcomes in the proposed INPA methods, managers have to identify the most appropriate parameters α. Thus, the presented INPA is more flexible, versatile, and convenient for optimal global solutions. Consequently, the proposed INPA is the most promising and reliable solving the SSP model.

Additionally, the multiobjective SSP is also solved by considering the type-1 fuzzy parameters. We have used the same data-set as summarized in Table 2 with single membership grades. The type-1 fuzzy parameters are transformed into their respective crisp version using the concept of [7]. The multiobjective SSP with type-1 fuzzy parameters is then solved using proposed INPA, and solution results are presented in Table 5. The various outcomes are generated at different degrees of vagueness (α). From Table 5, it can be observed that the values of all the objective function falls within the optimal ranges $\underline{O}_1 = 59021$, $\overline{O}_1 = 82513$, $\underline{O}_2 = 389$, $\overline{O}_2 = 552$ and $\underline{O}_3 = 693$, $\overline{O}_3 = 936$, respectively. Moreover, Table 5 reflects that using the type-2 fuzzy parameters, all the objectives' values are better than the type-1 fuzzy parameters. Since type-2 fuzzy parameters involve a set of secondary membership grades, the possibility or chances for risk violation becomes very less or negligible as compared to type-1 fuzzy parameters. In the type-1 fuzzy set, the corresponding membership grades are depicted by a single value, which is constant, whereas in the type-2 fuzzy system, a set of secondary membership grades corresponding to each primary membership function is considered. In both cases (using type-2 and type-1 fuzzy parameters), as the degree of vagueness increases, the objective functions reach their worst solution and vice-versa. When the decision-maker(s) is much concerned about the uncertainty and pays more attention to the risk violation, the objectives yield in worst outcomes due to the less achievement in the overall satisfaction level. By considering the type-2 fuzzy parameters, the decision-makers can determine the better solution results and overall satisfaction level.

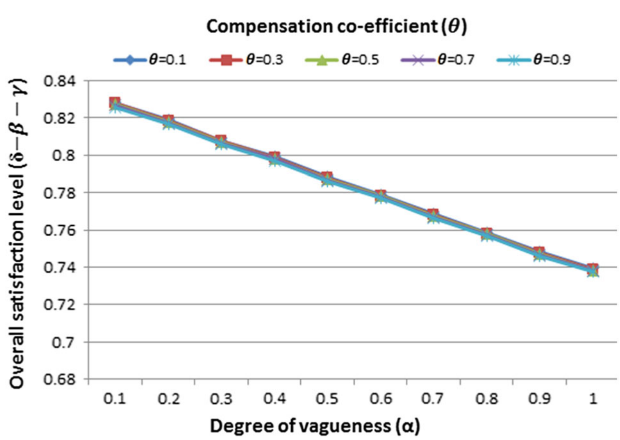

Fig. 1 Overall satisfaction level $(\delta - \beta - \gamma)$

6 Conclusions

This study presented the multiobjective SSP with type-2 triangular fuzzy parameters. The two defuzzification methods are suggested to transform the T-2TF parameters into the usual fuzzy one. First, the CV-based reduction method and another one are based on the nearest interval approximation technique with their robustness properties. Both the techniques are applied to convert the T-2TF parameters into their crisp version. The opportunity to generate the various solution results at a different values of α is presented. Further, a novel INPA is proposed to solve the crisp multiobjective SSP under the neutrosophic environment. The indeterminacy degree is incorporated while obtaining optimal global solutions. A variety of overall satisfaction levels at different compensation co-efficients θ is also depicted for selecting the most promising solution set.

Table 5 Comparison of solution results with respect to type-2 and type-1 fuzzy parameters

Degree of vagueness	Using type-2 fuzzy parameters			Using type-1 fuzzy parameters		
α	Min. O_1	Min. O_2	Min. O_3	Min. O_1	Min. O_2	Min. O_3
0.1	59184	393.04	701.63	60023	405.62	723.91
0.2	59191	402.68	722.96	61289	421.65	751.23
0.3	59706	417.27	763.91	62914	434.44	782.36
0.4	62389	429.51	788.31	63952	451.63	797.12
0.5	65028	443.89	804.29	67215	476.95	816.89
0.6	69384	471.41	831.47	71427	487.32	842.96
0.7	73906	494.13	866.22	75263	501.23	881.49
0.8	77826	511.34	895.61	79724	519.85	907.24
0.9	80508	531.45	911.76	81927	539.67	919.41
1	82229	543.25	927.68	82481	549.87	932.56

Some more metrics regarding the type-2 fuzzy parameters, such as the defuzzification technique using the centroid method, are left untouched. For future research, it can be further extended for interval-valued T-2TF parameters. The presented study can be applied to different real-life problems such as inventory control, transportation and assignment problems, supply chain management to manage the possibility of degrees under hesitation.

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Compliance with Ethical Standards

Conflict of interest All authors declare no conflict of interest.

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