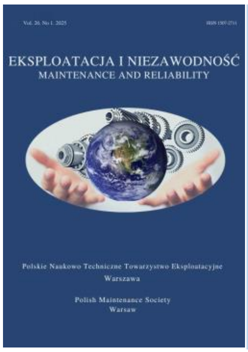

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An uncertain programming model for fixed charge transportation problem with item sampling rates

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Highlights

- Introduces two new parameters, product sampling pass rate and carbon emissions.
- The concepts of expected value model and chance-constrained model are proposed.
- A multi-objective analysis method and an improved sparrow algorithm are proposed.
- The performance of the improved sparrow algorithm is significantly improved.

Abstract

This paper analyzes the transportation issue involving multiple objectives and items with fixed costs amid uncertainty, which aims to increase net profit while minimizing carbon emissions, to determine an optimal product shipping strategy. This paper introduces the use of uncertain theory to address the transportation dilemma, considering various challenges such as potential uncertainties during the actual transport process. It involves defining variables such as supply, demand and the rate of product sampling qualification as uncertain factors, constructing mathematical models, and deriving the corresponding model as well as the respective equivalent form by means of uncertainty theory. A linear weighted method is adopted to reflect the significance of each objective as identified by policymakers and suggest a sparrow optimization algorithm combined with butterfly search for numerical experiments to discover the optimal solution. This demonstrates the practicality and effectiveness of the proposed models.

Keywords
uncertainty, multi-objective analysis, uncertain programming, intelligent algorithm, fixed charge

1. Introduction

Against the background of global economic integration, the expansion of the transportation sector across the globe has catalyzed the rapid growth of the logistics industry, underlining its increased importance in both manufacturing and everyday life. Transportation serves as a crucial component in the logistics chain, significantly influencing the national economy [1,2,3,4]. The classic transportation problem, first identified by Hitchcock in 1941 [5], is a well-established optimization challenge. It requires decision-makers to formulate efficient transportation strategies ensuring that the total cost of moving goods from their origin to the intended destination is kept to a minimum [6]. Generally, the TP involves two types of constraints: supply and demand constraints. The solid transport problem builds upon the conventional challenges of solid transport, an idea initially introduced by Haley [7]. It introduces three main categories of constraints: supply, demand, and transportation. The transportation constraint focuses on the method of moving the product from its starting point to its endpoint. In the STP, these constraints are analyzed through a spatial lens, leading to the development of the three-

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dimensional STP. Later, Qiu et al. [8] offered an approach based on neutrosophic logic to solve the neutrosophic solid transportation problem. In addition, Prathyusha et al. [9] developed hierarchical sequential goal planning techniques to tackle the two-objective solid transport problem.

The Fixed Charge Transportation Problem (FCTP) is classified under the umbrella of traditional transportation issues. It was first proposed by Hirsch and Dantzig et al. [10]. FCTP considers transportation costs, introducing a fixed charge as an additional expense. These extra costs might consist of tolls, vehicle rental charges, permit fees, and more, all of which do not depend on the amount of goods transported. If the fixed charges are not taken into account, this can lead to the selection of options with high fixed charges, which do not make full use of transport resources and lead to problems such as long transport distances and lower loading rates, which in turn increase the volume of road traffic, emissions and other environmental burdens, and reduce the efficiency of transport. Following this introduction, a growing body of research has emerged around the topic. Ghosh et al. [11] uses fuzzy programming method and other methods to find the Pareto optimal solution of this transportation problem. [12] proposed a two-stage fixed-charge transportation model, introducing three algorithms that utilize priority coding. Buson et al. [13] developed a mathematical heuristic method to tackle the complexities of large-scale transportation problems with fixed charges, demonstrating through comparative experiments that this approach rapidly yields high-quality, nearly optimal solutions. ldrissi et al. [14] studied the effect of various adaptation operators in FCTP and introduced a new crossover operator (IPX) aimed at finding the optimal solution.

In transportation issues, all variables are typically treated as deterministic. However, the complex networks and numerous links characteristic of transportation organizations mean their operations are influenced by various uncertainties, including road conditions, weather factors, and fluctuations in product supply and demand. Therefore, a multitude of researchers have explored the dynamics of traffic under uncertain conditions. For instance, Maity et al. [15] evaluated transportation problems including multiple objectives in uncertain environments. Midya and Roy [16] proposed a transportation model that integrates multiple objectives, indices, and stochastic components, alongside a fixed charge and a singular destination, employing fuzzy programming methods for resolution. In scenarios limited by a single source, [17] established a simple approximation method, providing a foundation for deriving initial solutions.

Fuzzy set theory serves as a mathematical tool for characterizing and manipulating uncertain and vague data, enabling the quantification of such information for further analysis and inference [18]. This is particularly relevant in transportation, where demand and supply often exhibit uncertainties, more so in practical scenarios where they display ambiguity. Fuzzy set theory offers a methodology for describing this ambiguity, facilitating the modeling and analysis of indistinct demand and supply patterns. Upmanyu et al. [19] introduced an innovative method for handling objective values composed of multiple fractions with fuzzy values. Liu et al. [20] developed a transportation model that addresses multiple objectives and integrates uncertainty in the production-sales framework, which was streamlined into a single-objective linear programming model using the maximin approach and then resolved. Effati et al. [21] unveiled a cutting-edge fuzzy neural network model aimed at tackling fuzzy linear programming problems encountered in real-world engineering scenarios.

Frequency is often considered a collection of observations from a random occurrence. In probability theory, the probability of an event occurring can be approximated by tallying how frequently that event has been observed across numerous trials and experiments. This method of estimation is grounded in empirical data and draws upon the law of large numbers, suggesting that the event's frequency will approach its probability as the number of trials increases. However, in certain situations, the application of probability theory may not be practical due to the lack of accessible, adequate, or accurate data. For instance, in the context of natural disasters, accidents, or other hard-to-measure phenomena, acquiring enough reliable data for probability calculations proves challenging. Persisting in applying probability theory to analyze these types of empirical data from experts [22] can lead to markedly different conclusions. In transportation issues, variables such as the cost of transport, duration, and the volume of goods required versus dispatched present significant challenges for measurement due to a range of factors. To address cognitive uncertainties, Liu [23] introduced the concept of uncertain theory, further optimized in

[24]. The outcomes of uncertain theory research have found broad application across various fields lately, especially in uncertain risk mitigation [25,26,27], strategies for financial investments [28,29,30], decisions in supply chain management [31,32,33], and in the field of statistics [34,35]. For more applications of uncertainty theory to transportation problems, see references [36,37].

Uncertain theory has gained significant traction in addressing transportation problems, where various risks and uncertainties, such as potential loss or damage to goods or fluctuating demands for transportation, are prevalent. Mou [38] devised an uncertain programming model that simplifies these issues into a model with a single-objective based on uncertain opportunity constraints. Roy [39] et al. analyzed the complexity of transportation problems characterized by dual uncertainties, multiple objectives, and numerous items with fixed charges.

As mentioned above, the transportation problem under uncertain environment has been widely studied. People usually treat supply and demand, fixed cost, etc. as uncertain variables, and take maximizing profit or shortest transportation time as goals to find an optimal transportation scheme. The text provided delves into the complexities of the transportation problem in the framework of maximizing profits while also addressing the multifaceted nature of such issues, including considerations such as costs, time, and safety of cargo. It highlights the necessity of adopting a multi-objective to ensure a balanced and comprehensive strategy, especially in light of global warming challenges and the push for a dual-carbon policy aimed at reducing carbon emissions. This policy shift prompts companies to incorporate environmental considerations into their decision-making processes, especially regarding carbon emissions during the transportation of goods. The variability of emissions, influenced by factors such as vehicle type, fuel efficiency, and cargo nature, necessitates a sophisticated approach to planning. In a volatile market environment, in order to help companies to better predict and control their transportation costs and gain greater profits, as well as to optimize the use of transportation resources, improve transportation efficiency, and reduce energy consumption and carbon emissions, among other things, this study proposes a novel model that incorporates these diverse elements, utilizing uncertain theory to balance profit maximization with carbon emission reduction. The model introduces new parameters, such as the product sampling pass rate and carbon emissions, to adapt to current needs and mitigate potential damage to cargo during transit. By converting the model into an expected value model and a chance-constrained model, the research establishes deterministic models that are then solved, followed by numerical tests and analysis to evaluate the efficacy of the proposed solutions.

In summary, the primary contributions of this research are as follows: taking into account the various problems in actual transportation, in order to help companies to obtain greater profits while optimizing the use of transportation resources, an innovative model for fixed-charge transportation problem is developed through a mathematical modeling approach, enhanced by introducing new parameters for product sampling pass rate and carbon emissions, which aims to maximize net profit while minimizing CO2 emissions during vehicle transportation, to determine the optimal product transportation strategy. Establish the corresponding expected value model and chance-constrained model through the knowledge of uncertainty theory, and derive the corresponding equivalent model for solution. Subsequently, a multi-objective analysis method is introduced to transform a multiple-objective transport problem proposed in this study into a simplified single-objective transport problem, and an improved sparrow search algorithm (BFSSA) is proposed to solve it. The study culminates in numerical experiments and analysis through MATLAB to assess the models' performance. The experimental results show that the improved algorithm (BFSSA) outperforms the original algorithm (SSA) in seeking the optimal solution and has better performance. This paper assesses the impact of various practical aspects of the transportation process, which not only increases profit margins, but also reduces negative impacts on the environment such as carbon emissions, making the results of the study more relevant and realistic.

In Section 2, the foundational principles of uncertainty theory are introduced. Section 3 is dedicated to providing a detailed description of the problem, including both the notation and the mathematical formulation of the issue being evaluated in this paper. Section 4 outlines two distinct models: the expected value model and the chance-constrained model. In Section 5, the uncertainty theory is applied to derive the corresponding determinate model. Section 6 recommends a method for transforming the multi-objective optimization problem into a problem with a single objective, alongside proposing an enhanced algorithm based on our theoretical findings. Numerical experiments are then conducted in Sections 7 to evaluate the performance of the proposed algorithms through an analysis of the experimental results.

2. Preliminary

Uncertainty theory is primarily employed to address and characterize the nature of uncertainty and fuzziness. This theory acknowledges the challenges decision-makers face when they encounter various incomplete and ambiguous pieces of information during the processes of information processing and decision-making, complicating the achievement of clear-cut decisions. As a result, uncertain theory offers systematic methods for quantifying and managing this uncertainty, thereby improving the handling of vague and partial information. To put it succinctly, functions measured in an uncertain environment are referred to as uncertain variables.

Let $\mathscr{L}$ represent σ -algebra on a set Γ that is not empty. Each of the elements in $\mathscr{L}$ is referred to as an event Λ. An uncertainty measure means a function, which is mapped from $\mathscr{L}$ to a gap [0,1]. Every event Λ has a probability, that it will occur; this likelihood is known as the measure $\mathcal{M}\{\Lambda\}$. Liu defines a triple $(\Gamma, \mathscr{L}, \mathscr{M})$ consisting of a non-empty set Γ , σ -algebra $\mathscr{L}$ and an uncertainty measure $\mathscr{M}$ as an uncertainty space.

For a better characterization and description of the uncertain phenomenon, Liu defines the uncertain variable. Function ξ is considered measurable when it maps the uncertain space $(\Gamma, \mathscr{L}, \mathscr{M})$ to the list of actual numbers $\mathbb{R}$, i.e., for an arbitrary Borel set $\mathbb{B}$, set

$$\{\xi \in \mathbb{B}\} = \{\gamma \in \Gamma\} | \xi(\gamma) \in \mathbb{B}.$$

is an event, which is considered to be a variable that is characterized by uncertainty, and the uncertain distribution Φ is defined as

$$\Phi(x) = \mathcal{M}\{\xi \le x\}.$$

The inverse function $\Phi^{-1}(\alpha)$ is referred to as the inverse uncertainty distribution of ξ when ξ is an uncertain variable with a regular uncertainty distribution $\Phi(x)$.

Theorem 1 Let $\xi_1, \xi_2, \cdots, \xi_n$ be a set of independent uncertain variables and their uncertain distributions $\Phi_1(x), \Phi_2(x), \cdots, \Phi_n(x)$ are all regular. If the function $f(x_1, x_2, \cdots, x_n)$ is mono-increasing for $x_1, x_2, \cdots, x_m$ and mono-decreasing for $x_{m+1}, x_{m+2}, \cdots, x_n$, then

$$\Psi^{-1}(\alpha) = f(\Phi_1^{-1}(\alpha), \cdots, \Phi_m^{-1}(\alpha), \Phi_{m+1}^{-1}(1-\alpha), \cdots, \Phi_n^{-1}(1 - \alpha))$$

is the inverse uncertainty distribution of the indeterminate variable $\xi = f(\xi_1, \xi_2, \cdots, \xi_n)$, where α stands for an integral variable from 0 to 1.

Theorem 2 Let ξ be an uncertain variable and have a regular uncertainty distribution $\Phi(x)$. If its expectation exists, then we have

$$E[\xi] = \int_0^1 \Phi^{-1}(\alpha) d\alpha$$

where α stands for an integral variable from 0 to 1.

Theorem 3 (LiuandHa[40]) Let $\xi_1, \xi_2, \cdots, \xi_n$ be independent uncertain variables and their uncertainty distributions $\Phi_1(x), \Phi_2(x), \cdots, \Phi_n(x)$ are regular. If the function $f(x_1, x_2, \cdots, x_n)$ is simple increasing for $x_1, x_2, \cdots, x_m$ and simple decreasing for $x_{m+1}, x_{m+2}, \cdots, x_n$, the expectation of the indeterminate variable $\xi = f(\xi_1, \xi_2, \cdots, \xi_n)$ is

$$E[\xi] = \int_0^1 f(\Phi_1^{-1}(\alpha), \cdots, \Phi_m^{-1}(\alpha), \Phi_{m+1}^{-1}(1-\alpha), \cdots, \Phi_n^{-1}(1-\alpha)) d\alpha$$

where α stands for an integral variable from 0 to 1.

3. Problem Description

This section offers an in-depth analysis of the fixed-charge transportation problem in an uncertain context. Taking into account the actual situation in the transportation process, such as the damage caused by road bumps, the generation of fixed charges such as tolls, vehicle rental fees and other uncertain situations, some parameters are set as uncertain parameters to seek an optimal transportation scheme. Thereafter, the notations and assumptions are presented that will underpin the mathematical model.

Notations

i: quantity of starting points ($i = 1,2, \ldots, m$)

j: quantity of destinations ($j = 1,2, \ldots, n$)

k: type of transportation mode ($k = 1,2, \ldots, l$)

p: type of item ($p = 1,2, \ldots, q$)

a_i^p: quantity of item p from starting points i that may be shipped and sold

b_j^p: quantity of item p needed in destination j

c_{ijk}^p: unit transportation cost of item p from origins i to destinations j via means of transportation k

f_{ijk}: the fixed charge of conveyance k

λ_{ijk}^p: the passing rate of sampling inspection of item p from source i to destination j via conveyance k

ω_i^p: the purchase price for item p at origin i

η_k: transportation capacity of conveyance k

e_k : carbon emissions per unit of item transported via means of transportation k

ξ_j^p: the price at which item p is being sold in destination j

x_{ijk}^p: amount of item p that was transported from origin i to destination j by means of conveyance k

Assumptions:

1. $a_i^p > 0\,, b_j^p > 0\,, \eta_k > 0\ \forall i, j, p, k.$
2. The product does not deteriorate during transportation.
3. Each variable considered is positive in its component.
4. The units of a_i^p, b_j^p, η_k and x_{ijk}^p are cubic meters, the units of f_{ijk} are dollars, the units of e_k are kilograms per cubic meter. c_{ijk}^p, ξ_j^p and ω_i^p are dollars per cubic meter.

Then the mathematical representation of the multi-objective FCTP is presented, involving m origins, n destinations, l transportation modes, and q items to be transported between any given origin and destination. Thus, the FCTP can be constructed as

$$(M_1)\begin{cases} max\,i\,mize\ Z_1 = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{l}\sum_{p=1}^{q}(\xi_j^p\lambda_{ijk}^p - c_{ijk}^p - \omega_i^p)\,x_{ijk}^p \\ \qquad\qquad - \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{l} f_{ijk}\,y_{ijk} & (1) \\ min\,i\,mize\ Z_2 = \sum_{k=1}^{l}(e_k \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{p=1}^{q} x_{ijk}^p) & (2) \\ s.t. \\ \sum_{j=1}^{n}\sum_{k=1}^{l} x_{ijk}^p \le a_i^p & (3) \\ \sum_{i=1}^{m}\sum_{k=1}^{l} \lambda_{ijk}^p\,x_{ijk}^p \ge b_j^p & (4) \\ \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{p=1}^{q} x_{ijk}^p \le \eta_k & (5) \end{cases}$$

where $x_{ijk}^p \ge 0\,, y_{ijk} \in \{0,1\}$, the overall model is referred to as model M_1.

The network chart pertaining to this transportation problem is depicted in Fig. 1. This illustration provides a view of a network diagram featuring two origins, two destinations, and two different items being transported using two different modes of transportation. Indeed, the fixed charge transportation problem has a wide range of applications in areas such as logistics and supply chain management, urban transportation planning, and power transmission networks.

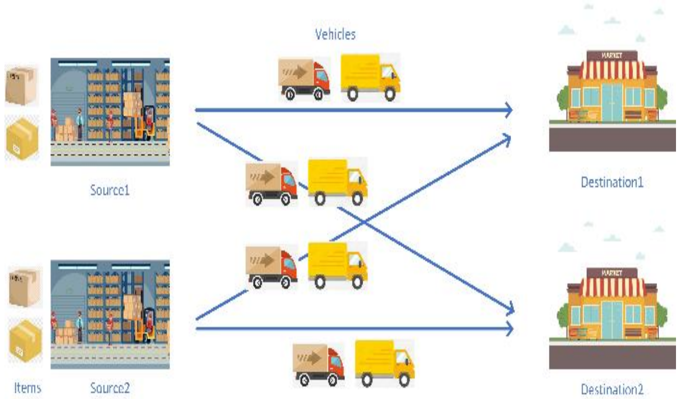

Fig.1. Network diagram of multi-objective transportation problem.

In our indicated FCTP, two primary objectives functions are introduced. The first objective function (1) denotes the net benefit, considering the deduction of purchase price, transportation expenses, and fixed charges. This calculation must also factor in the product's sampling rate at each destination, acknowledging the potential for item damage due to irregular road conditions and constraints imposed by the transportation carrier. The objective function (2) focuses on the reduction of carbon emissions during item transport. To balance the supply and demand effectively, constraints (3) and (4) ensure that the volume of items shipped meets the needs of suppliers and retailers alike, where constraint (4) specifically refers to the quantity of items p shipped to a retailer j from various suppliers i through all modes of transport k after sampling inspection, the quantity of qualified items is more than the items required by retailer j to meet the oversupply. In addition, constraint (5) represents the limitations associated with the transportation carrier.

In addition, y_{ijk} is a binary decision variable and indicates that, if $x_{ijk}^p > 0$, an item is carried from origin i to destination j by means of transportation k, thus a fixed charge should be included in the total transport cost, at which point

$y_{ijk} = 1$, otherwise $y_{ijk} = 0$.

4. Uncertain mathematical models

In scenarios characterized by uncertainty, a_i^p, b_j^p, c_{ijk}^p, f_{ijk}, λ_{ijk}^p, ω_i^p, η_k, e_k are treated as independent uncertainties. Our approach to addressing this complexity involves various modeling strategies. This paper focuses on the expected value model and the chance-constrained model as methodologies for analyzing the FCTP.

4.1. Expected value model

The expected value model (EVM) calculates the average of uncertain variables, offering a quantitative assessment of uncertainty. It reflects the quantitative value on uncertainty. It has been widely applied in numerous real-world problems. Our objective is to elevate the goal function to its optimal level, considering the expected values and adhering to several constraints related to these expectations.

Thus, EVM is expressed as:

$$(M_2)\begin{cases} max\, \mathrm{E}\,[Z_1] & (6)\\ min\, \mathrm{E}\,[Z_2] & (7)\\ s.t. & \\ E\left[\sum_{j=1}^{n}\sum_{k=1}^{l} x_{ijk}^p - a_i^p\right] \le 0 & (8)\\ E\left[\sum_{i=1}^{m}\sum_{k=1}^{l} (\lambda_{ijk}^p x_{ijk}^p) - b_j^p\right] \ge 0 & (9)\\ E\left[\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{p=1}^{q} x_{ijk}^p - \eta_k\right] \le 0 & (10) \end{cases}$$

It is critical to ensure that constraints (8)-(10) comply with established guidelines.

4.2. Chance-constrained model

In practical applications, various risks are omnipresent. Therefore, to craft an ideal transpor-tation schedule, it is crucial for policymakers to establish a confidence level beforehand. This approach acknowledges that decisions might not always meet established criteria under unfavorable conditions. Hence, a guideline is adopted allowing for some deviation from these criteria, provided that the probability of the decision meeting the criteria exceeds a minimally acceptable confidence level. For instance, setting the confidence level at 0.90 means the decision-maker must predict a target value, denoted as $\bar{f}$ Should this transportation strategy be implemented, it is critical to ensure that the target value surpasses the predicted value, with a confidence level exceeding 0.90 , i.e.$\mathcal{M}\{f(x) \ge \bar{f}\} \ge 0.9$. Therefore, the chance-constrained model (CCM) is formulated as:

$$(M_3)\begin{cases} max\ \overline{Z_1} & (11)\\ min\ \overline{Z_2} & (12)\\ s.t. & \\ \mathcal{M}\{Z_1 \ge \overline{Z_1}\} \ge \alpha_1 & (13)\\ \mathcal{M}\{Z_2 \le \overline{Z_2}\} \ge \alpha_2 & (14)\\ \mathcal{M}\left\{\sum_{j=1}^{n}\sum_{k=1}^{l} x_{ijk}^p \le a_i^p\right\} \ge \alpha_i^p, i = 1,2,\dots,m & (15)\\ \mathcal{M}\left\{\sum_{i=1}^{m}\sum_{k=1}^{l} \lambda_{ijk}^p\, x_{ijk}^p \ge b_j^p\right\} \ge \beta_j^p, j = 1,2,\dots,n & (16)\\ \mathcal{M}\left\{\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{p=1}^{q} x_{ijk}^p \le \eta_k\right\} \ge \theta_k, k = 1,2,\dots,l, & (17) \end{cases}$$

where α_1,α_2,α_i^p,β_j^p,θ_k all represent confidence levels.

5. Equivalent transitions

The FCTP model incorporates several uncertain variables, posing challenges in calculation and simulation. To streamline the computational effort, these variables can be converted into a deterministic format. Uncertain models usually involve probability and random variables, whereas deterministic models base their calculations on definite values. Deterministic variables are easier to model and compute mathematically, which helps decision makers better assess possible outcomes and make rational decisions, reduces the complexity of the solution, and improves the efficiency of the solution.

5.1. The expected value model of equivalent transformation

Theorem 4 We hypothesized that in an uncertain environment, a_i^p, b_j^p, c_{ijk}^p, f_{ijk}, λ_{ijk}^p, ω_i^p, η_k, e_k are independent uncertain variables which each have a regular uncertainty distribution Ψ_i^p,Φ_j^p,Π_{ijk}^p,Θ_{ijk},Λ_{ijk}^p,Ξ_i^p,τ_k,γ_k. Then the following model is the same as model M_2:

$$
(M_4)\begin{cases}
max\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{l}\sum_{p=1}^{q}\left\{\xi_j^p\int_0^1(\Lambda_{ijk}^p)^{-1}(\alpha)\,d\,\alpha\right. \\
\left.-\int_0^1(\Pi_{ijk}^p)^{-1}(1-\alpha)d\alpha-\int_0^1(\Xi_i^p)^{-1}(1-\alpha)\,d\,\alpha\right\}x_{ijk}^p \\
-\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{l}y_{ijk}\int_0^1(\Theta_{ijk})^{-1}(1-\alpha)\,d\,\alpha \qquad (18) \\
min\sum_{k=1}^{l}(\int_0^1(\gamma_k)^{-1}(\alpha)\,d\,\alpha\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{p=1}^{q}x_{ijk}^p) \qquad (19) \\
s.t. \\
\sum_{j=1}^{n}\sum_{k=1}^{l}x_{ijk}^p-\int_0^1(\Psi_i^p)^{-1}(1-\alpha)\,d\,\alpha\le 0 \qquad (20) \\
\quad\int_0^1(\Phi_j^p)^{-1}(\alpha)\,d\,\alpha- \\
\sum_{i=1}^{m}\sum_{k=1}^{l}(\int_0^1(\Lambda_{ijk}^p)^{-1}(1-\alpha)\,d\,\alpha)\,x_{ijk}^p\le 0 \qquad (21) \\
\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{p=1}^{q}x_{ijk}^p-\int_0^1(\tau_k)^{-1}(1-\alpha)\,d\,\alpha\le 0 \qquad (22)
\end{cases}
$$

Proof : according to $E[a\xi+b\eta]=aE[\xi]+bE[\eta]$ and Theorem 3, we have

$$
E\left\{\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{l}\sum_{p=1}^{q}(\xi_j^p\lambda_{ijk}^p-c_{ijk}^p-\omega_i^p)\,x_{ijk}^p\right\}
$$

$$
=\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{l}\sum_{p=1}^{q}(\xi_j^pE(\lambda_{ijk}^p)-E(c_{ijk}^p)-E(\omega_i^p))x_{ijk}^p
$$

$$
=\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{l}\sum_{p=1}^{q}(\xi_j^p\int_0^1(\Lambda_{ijk}^p)^{-1}(\alpha)\,d\,\alpha
$$

$$
-\int_0^1(\Pi_{ijk}^p)^{-1}(1-\alpha)\,d\,\alpha-\int_0^1(\Xi_i^p)^{-1}(1-\alpha)\,d\,\alpha)x_{ijk}^p \qquad (23)
$$

Similarly, the rest of the formulas are derived in the same way.

5.2 The chance-constrained model of equivalent transformation

Lemma 1 Consider$\xi_1,\xi_2,\cdots,\xi_n$as independent variables with uncertainty, and their uncertain distributions $\Phi_1,\Phi_2,\cdots,\Phi_n$ are regular. If the function $f(\xi_1,\xi_2,\cdots,\xi_n)$ is monoincreasing exclusively for $\xi_1,\xi_2,\cdots,\xi_n$, then

$$\mathcal{M}\{f(\xi_1,\xi_2,\cdots,\xi_n)\le\bar{f}\}\ge\alpha$$

is the same as

$$f(\Phi_1^{-1}(\alpha),\cdots,\Phi_n^{-1}(\alpha))\le\bar{f},$$

Among them, α is the confidence level.

Theorem 5 Under the assumptions of Theorem 4, the model M_3 can be converted to

$$
(M_5)\begin{cases}
min[\Phi_N^{-1}(\alpha_1)] \qquad (24) \\
min[\Phi_{Z_2}^{-1}(\alpha_2)] \qquad (25) \\
s.t. \\
\sum_{j=1}^{n}\sum_{k=1}^{l}x_{ijk}^p-(\Psi_i^p)^{-1}(1-\alpha_i^p)\le 0 \qquad (26) \\
(\Phi_j^p)^{-1}(\beta_j^p)-\sum_{i=1}^{m}\sum_{k=1}^{l}x_{ijk}^p\,(\Lambda_{ijk}^p)^{-1}(1-\beta_j^p)\le 0 \qquad (27) \\
\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{p=1}^{q}x_{ijk}^p-(\tau_k)^{-1}(1-\theta_k)\le 0 \qquad (28)
\end{cases}
$$

where

$$
N=-Z_1=\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{l}\sum_{p=1}^{q}(c_{ijk}^p+\omega_i^p
$$

$$
-\xi_j^p\lambda_{ijk}^p)\;\;x_{ijk}^p+\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{l}f_{ijk}\,y_{ijk} \qquad (29)
$$

and$(\Psi_i^p)^{-1}$,$(\Phi_j^p)^{-1}$,$(\Pi_{ijk}^p)^{-1}$,$(\Theta_{ijk})^{-1}$,$(\Lambda_{ijk}^p)^{-1}$,$(\Xi_i^p)^{-1}$,$(\tau_k)^{-1}$, $(\gamma_k)^{-1}$ is the inverse distribution of Ψ_i^p,Φ_j^p,Π_{ijk}^p,Θ_{ijk},Λ_{ijk}^p,Ξ_i^p,τ_k,γ_k respectively, $\Phi_N^{-1}(\alpha_1)$,$\Phi_{Z_2}^{-1}(\alpha_2)$ are the inverse distributions of N and Z_2, and α_1,α_2,α_i^p,β_j^p,θ_k is the preset confidence level.

Proof: from equation (29), our objective function equation (11) can be changed into

$$
\begin{cases}
min\ \bar{N} \\
s.t. \\
\mathcal{M}\{N\le\bar{N}\}\ge\alpha_1.
\end{cases} \qquad (30)
$$

By Theorem 1 and Lemma 1, equation (30) is equivalent to

$$
\begin{cases}
min\ \bar{N} \\
s.t. \\
\Phi_N^{-1}(\alpha_1)\le\bar{N}
\end{cases} \qquad (31)
$$

which can be reduced to

$$
min\ \Phi_N^{-1}(\alpha_1)=\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{l}\sum_{p=1}^{q}\Big[\big(\Pi_{ijk}^p\big)^{-1}(\alpha_1)
$$

$$
+\big(\Xi_i^p\big)^{-1}(\alpha_1)-\xi_j^p(\Lambda_{ijk}^p)^{-1}(1-\alpha_1)\Big]\,x_{ijk}^p
$$

$$
+\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{l}y_{ijk}\big(\Theta_{ijk}\big)^{-1}(\alpha_1) \qquad (32)
$$

In order to analyze the multi-objective optimization problem more conveniently, the two objective functions are unified to find the minimum value. Therefore, the objective function equation (11) is transformed from maximizing to minimizing the value. The same is true for the transformation of the objective function equation (12).

For constraint (15), a_i^p is a monotonically increasing continuous function, then $-a_i^p$ is mono-tonically decreasing and a_i^p is an uncertain variable with its inverse uncertain distribution being $(\Psi_i^p)^{-1}$. By Lemma 1 and Theorem 1, the

$$\mathcal{M}\{\sum_{j=1}^{n}\sum_{k=1}^{l}x_{ijk}^p \leq a_i^p\} \geq \alpha_i^p \tag{33}$$

is the same as

$$\sum_{j=1}^{n}\sum_{k=1}^{l}x_{ijk}^p - (\Psi_i^p)^{-1}(1-\alpha_i^p) \leq 0 \tag{34}$$

Similarly, the remaining constraints are derived in the same way.

Therefore, the deterministic transformation of model M_5 is equivalent to

$$(M_6)\begin{cases} min\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{l}\sum_{p=1}^{q}\Big[\left(\Pi_{ijk}^p\right)^{-1}(\alpha_1) \\ +\left(\Xi_i^p\right)^{-1}(\alpha_1)-\xi_j^p\left(\Lambda_{ijk}^p\right)^{-1}(1-\alpha_1)\Big]x_{ijk}^p \\ +\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{l}y_{ijk}\left(\Theta_{ijk}\right)^{-1}(\alpha_1) & (35) \\ min\sum_{k=1}^{l}((\gamma_k)^{-1}(\alpha_2)\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{p=1}^{q}x_{ijk}^p) & (36) \\ s.t. \\ \sum_{j=1}^{n}\sum_{k=1}^{l}x_{ijk}^p-(\Psi_i^p)^{-1}(1-\alpha_i^p)\leq 0 & (37) \\ (\Phi_j^p)^{-1}(\beta_j^p)-\sum_{i=1}^{m}\sum_{k=1}^{l}x_{ijk}^p\,(\Lambda_{ijk}^p)^{-1}(1-\beta_j^p)\leq 0 & (38) \\ \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{p=1}^{q}x_{ijk}^p-(\tau_k)^{-1}(1-\theta_k)\leq 0 & (39) \end{cases}$$

where α_1,α_2,α_i^p,β_j^p,θ_k is the preset confidence level.

6. Solutions

This section presents an overview of a multi-objective analysis method: the linear weighted method, followed by an improved algorithm proposing in this paper. A flowchart on the overall structure of the research content method is shown in Fig . 2 below.

6.1. Linear weighted method

This study also introduces a multi-objective analysis method: the linear weighted method, and proposes an enhanced algorithm. The linear weighted method evaluates functions by assigning weights based on the relative importance of each objective. These weights are then linearly assembled to derive an optimal solution for the multi-objective problem[41].

Weights are assigned to each objective function according to their significance, ensuring the total of all weights equals 1. The objective functions are then multiplied by these weights to formulate the solution for the objective function.

$$U(X)=\sum_{i=1}^{m}w_i * f_i(x)$$

Model $U(X), X \in \mathbb{R}$ is solved to seek the best result， where w_i represents the weight coefficients and $f_i(x)$ represents each objective function.

In this study, a method of linearly weighted summation is employed to adjust the relative weight of each index in the overall weighting scheme, thereby transforming a multiple-objective transport problem into a simplified single-objective transport problem. This approach allows us to represent the importance of each objective according to the policy maker's perspective as a linear weighted sum.

The multi-objective function in this paper can be changed to by linear weighted method as

$$min\,U=-w_1Z_1+w_2Z_2 \tag{40}$$

For the EVM, it can be expressed as

$$(M_7)\begin{cases} min-w_1E[Z_1]+w_2E[Z_2] & (41) \\ s.t. \\ \sum_{j=1}^{n}\sum_{k=1}^{l}x_{ijk}^p-\int_0^1(\Psi_i^p)^{-1}\,(1-\alpha)\,d\,\alpha\leq 0 & (42) \\ \int_0^1(\Phi_j^p)^{-1}\,(\alpha)\,d\,\alpha-\sum_{i=1}^{m}\sum_{k=1}^{l}(\int_0^1(\Lambda_{ijk}^p)^{-1} \\ (1-\alpha)\,d\,\alpha)x_{ijk}^p\leq 0 & (43) \\ \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{p=1}^{q}x_{ijk}^p-\int_0^1(\tau_k)^{-1}\,(1-\alpha)\,d\,\alpha\leq 0 & (44) \end{cases}$$

For the CCM, it can be denoted as

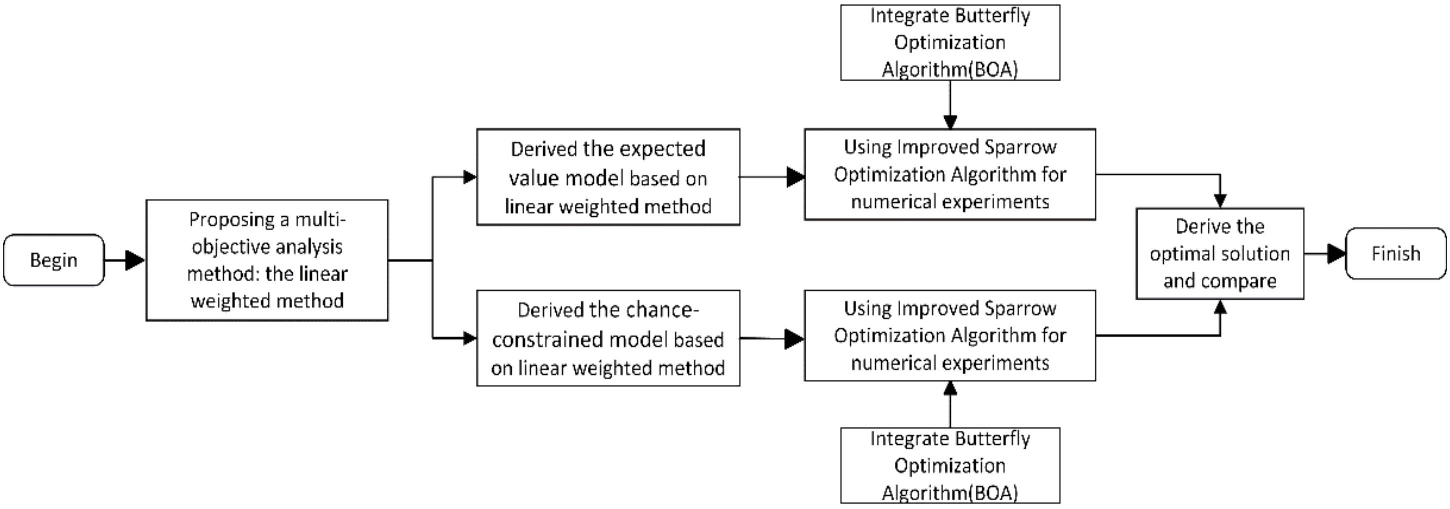

Fig. 2. General flowchart of the research methodology.

$$
(M_8)\begin{cases}
\min w_1 \overline{N} + w_2 \overline{Z_2} & (45)\\
s.t. & \\
\sum_{j=1}^{n}\sum_{k=1}^{l} x_{ijk}^{p} - (\Psi_i^p)^{-1}(1-\alpha_i^p) \le 0 & (46)\\
(\Phi_j^p)^{-1}(\beta_j^p) - \sum_{i=1}^{m}\sum_{k=1}^{l} x_{ijk}^{p}\,(\Lambda_{ijk}^{p})^{-1}(1-\beta_j^p) \le 0 & (47)\\
\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{p=1}^{q} x_{ijk}^{p} - (\tau_k)^{-1}(1-\theta_k) \le 0 & (48)
\end{cases}
$$

where w_1 and w_2 represent the weight coefficients corresponding to Z_1 and Z_2, respectively. For both models, it needs to be guaranteed that $w_1 + w_2 = 1, w_1, w_2 \in [0,1]$.

6.2. Heuristic Algorithm

Considering the complexity of the model, resolving it with conventional mathematical programming tools proves challenging. In response, a revised sparrow optimization algorithm (BFSSA) that integrates elements of the butterfly search mechanism is introduced. This innovation is motivated by the global update strategy of the butterfly algorithm, incorporating its unique individual-awareness ability into the sparrow algorithm, simulating the foraging and evasion strategies of butterfly flight limits the search process to a certain range, which helps to improve the accuracy of local search. This integration not only boosts the sparrow algorithm's capacity for optimization but also strengthens its ability to search globally, and avoids falling into the local optimal solution and failing to find the global optimal solution, and also improves the convergence speed.

The Sparrow Search Algorithm (SSA) draws its inspiration from the foraging behavior of sparrows [42]. Typically, sparrows are categorized into two roles while foraging: followers and finders. The finders are tasked with locating food and guiding the group to areas abundant in resources, thereby informing the direction of foraging activities. In contrast, followers rely on the finders for direction and then acquire their sustenance based on this guidance. Moreover, a select number of sparrows are designated as vigilants. These birds forego their own feeding opportunities to serve as an early warning system against potential threats, prioritizing the safety of the flock over personal nourishment. The position of the finder is updated using the formula provided below.

$$
X_{id}^{t+1} = \begin{cases} X_{id}^{t} \cdot exp\left[\dfrac{-i}{\alpha \cdot T}\right], \text{if } R_2 < ST \\ X_{id}^{t} + \Gamma \cdot L, \quad \text{if } R_2 > ST \end{cases}
$$

where X_{id}^{t} denotes , in the dth dimension, the location of the ith sparrow in the population at generation t and Trepresents the highest number of iterations. Γ is a stochastic number that meets the requirements of a standard normal distribution. α takes any number from 0 to 1. L represents a matrix with all elements of 1 and its size is $i \times d$. $R_2 \in [0,1]$ indicates early warning value while $ST \in [0.5,1]$ denotes a security value. In the revised algorithm, the search strategy of the butterfly algorithm is incorporated into the discoverer phase, applying the following equation when $R_2 \le ST$ is present:

$$
x_i^{t+1} = x_i^{t} + (r^2 \times g^* - x_i^{t}) \times f_i
$$

where f_i is the perception strength of the sparrow to the food; r is a random numeral between 0 and 1, and g^* stand for the overall optimal solution. In the detector search phase, the sparrow moves towards the food. Implementing a triangle wandering strategy is recommended while $R_2 \geq ST$ is on. This approach involves the sparrow encircling the food rather than moving straight towards it, thereby increasing its randomness. The triangle wandering strategy is detailed as follows:

$$L_1 = pos_b(t) - pos_c(t)$$

$$\vec{L_2} = rand() \times \vec{L_1}$$

where L_1 is the distance between the population and prey, and L_2 is the range of wandering steps of the population.

The following equation is then utilized to define the direction of travel :

$$\beta = 2 \times pi \times rand()$$

where β represents the direction of travel.

The following formula is then adopted to arrive at the position of the sparrow after it has wandered off.

$$P = L_1^2 + L_2^2 - 2 \times L_1 \times L_2 \times cos(\beta)$$

$$Pos_{new} = pos_b(t) + r \times P$$

Next, update the follower's position with the following formula:

$$X_{id}^{t+1} = \begin{cases} \Gamma \cdot exp\left[\dfrac{X_{w_d}^t - X_{id}^t}{i^2}\right], & \text{if } i > \dfrac{n}{2} \\ X_{p_d}^{t+1} + |X_{id}^t - X_{p_d}^{t+1}|A^+ \cdot L, \text{otherwise} \end{cases}$$

$X_{w_d}^t$ means the worst position of the sparrow at generation t. $X_{p_d}^{t+1}$ indicates the position where the population is most fit for the sparrow at generation $t+1$. A represents a one-row multi-dimensional matrix, where each element is 1 or -1. When $i > \frac{n}{2}$, it indicates that the ith joining sparrow was required to travel to other regions to forage. Conversely, this process can be interpreted as the joiner i seeking food near the current optimal position.

Approximately 10 to 20 percent of the population consists of early warners, whose positions are determined randomly through the following position update formula:

$$X_{id}^{t+1} = \begin{cases} X_{b_d}^t + \beta(X_{id}^t - X_{b_d}^t), & \text{if } f_i \neq f_g \\ X_{id}^t + K\left[\dfrac{X_{id}^t - X_{w_d}^t}{|f_i - f_w| + \delta}\right], \text{if } f_i = f_g \end{cases}$$

where, $X_{b_d}^t$ is the current globally optimal position, β is the exponent of the control step. $K$is a stochastic number between [-1,1] in which represents the movement direction of the sparrow. δ denotes a tiny constant. f_i means the adaptation value of the ith sparrow, f_g and f_w are the best and worst adaptation values of the currently population. In essence, when $f_i = f_g$, the early warning agent is positioned centrally in the population, it will continue to move closer to its companions for safety; otherwise, when $f_i \neq f_g$, it will adjust its position towards a safer location.

Thereby, the following Fig. 3 is how the BFSSA operates:

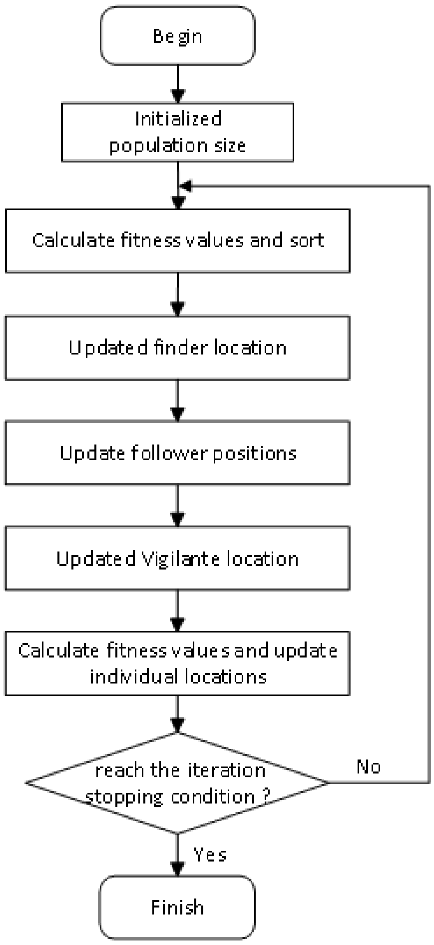

Fig. 3. Flow chart of BFSSA.

7. Numerical experiments and analysis of results

To verify the accuracy of the model, numerical experiments are conducted in this chapter. Our analysis involves the use of two types of transport vehicles (trucks and vans) to move two items from two starting points to two destinations. All variables with uncertainty are assumed to follow a linear distribution and are detailed in Tables 1 through 6. Our objectives seek to maximize the overall profit derived from the transport process while striving to reduce the carbon emissions produced. All simulations are performed using Matlab. In addition, the parameters of both algorithms are set as follows: Maxgeneration=2000, Popsize=50.

Table 1. Quantities of shipped items a_i^p and the purchase price ω_i^p.

	$i\backslash p$	1	2
a_i^p	1	(73,85)	(62,79)
	2	(75,90)	(64,78)
ω_i^p	1	(7,10)	(8,12)
	2	(8,12)	(6,10)

Table 2. Demand for items b_j^p and sale price ξ_j^p

	$j\backslash p$	1	2
b_j^p	1	(60,68)	(46,50)
	2	(50,56)	(40,52)
ξ_j^p	1	35	35
	2	38	34

Table 3. Unit transportation costs c_{ijk}^1 and c_{ijk}^2

	k	1		2	
	$i\backslash j$	1	2	1	2
c_{ijk}^1	1	(0.07,0.10)	(0.11,0.13)	(0.15,0.16)	(0.11,0.14)
	2	(0.10,0.13)	(0.11,0.15)	(0.14,0.18)	(0.16,0.18)
c_{ijk}^2	1	(0.14,0.16)	(0.13,0.15)	(0.13,0.18)	(0.12,0.15)
	2	(0.15,0.19)	(0.10,0.14)	(0.09,0.15)	(0.09,0.12)

Table 4. Sampling and inspection pass rate λ_{ijk}^1 and λ_{ijk}^2

	k	1		2	
	$i\backslash j$	1	2	1	2
λ_{ijk}^1	1	(0.94,0.96)	(0.96,0.98)	(0.92,0.96)	(0.92,0.95)
	2	(0.94,0.97)	(0.94,0.97)	(0.92,0.93)	(0.90,0.93)
λ_{ijk}^2	1	(0.90,0.92)	(0.90,0.92)	(0.95,0.98)	(0.95,0.96)
	2	(0.93,0.95)	(0.95,0.98)	(0.90,0.92)	(0.92,0.96)

Table 5. Fixed charges f_{ijk}

	k	1		2	
	$i\backslash j$	1	2	1	2
f_{ijk}	1	(3,7)	(8,9)	(4,6)	(4,7)
	2	(6,9)	(7,9)	(5,7)	(4,8)

Table 6. The conveyance capacity η_k and per unit carbon emissions e_k.

k	1	2
η_k	(152,162)	(161,175)
e_k	(0.4,0.7)	(0.5,0.6)

Table 7. Optimal solutions of the expected value model.

AL	TP	TE	TL	Optimal solution
SSA	6681.2	152.3	276.8	$x_{111}^1=18.8198, x_{111}^2=16.4569, x_{112}^1=20.0778, x_{112}^2=15.6694$ $x_{121}^1=15.7381, x_{121}^2=16.0414, x_{122}^1=17.9330, x_{122}^2=15.9485$ $x_{211}^1=19.0320, x_{211}^2=15.8952, x_{212}^1=20.8603, x_{212}^2=17.4703$ $x_{221}^1=16.8626, x_{221}^2=14.5973, x_{222}^1=18.7980, x_{222}^2=16.6269$
BFSSA	7525.7	166.6	303.0	$x_{111}^1=0.0232, x_{111}^2=0.2756, x_{112}^1=6.2629, x_{112}^2=53.8266$ $x_{121}^1=39.5528, x_{121}^2=0.1233, x_{122}^1=33.1603, x_{122}^2=16.2742$ $x_{211}^1=64.4764, x_{211}^2=1.2412, x_{212}^1=0.6709, x_{212}^2=7.9398$ $x_{221}^1=15.5063, x_{221}^2=35.2518, x_{222}^1=1.8456, x_{222}^2=26.5605$

An enhanced sparrow optimization algorithm is employed to solve a specific fixed-charge transportation problem. The outcomes from two different models are presented through a linear weighted sum programming method. Considering that the objective functions are total profit and total carbon emissions, respectively, the weight values are set to w_1=0.8,w_2=0.2 for combining according to the actual situation, and the optimal results obtained by the algorithm are displayed in the following table. Where AL stands for intelligent algorithm, TP represents total profit (Z1), TE denotes total carbon emission (Z2), and the value x_{ijk}^p in the optimal solution corresponds to the decision variables' values. TL signifies the aggregate of the decision variables x^p_{ijk}. TP, TE, and TL are in dollars, kilograms, and cubic meters, respectively.

As shown in Table 7, it is clear that BFSSA outperforms SSA. To further compare the algorithms, The relative error (RE) can be used as a measure, denoted as:

$$RE = \frac{\sum(f - f^*)}{nf^*} \times 100\%$$

where f^* denotes the optimal value, f denotes the value of the objective function, n is the number of tests.

When analyzed from the point of view of relative error in Table 8, the relative error value of BFSSA is lower than that of SSA, and it is clear that BFSSA is superior to SSA.

Table 8. Comparison of RE of Algorithms.

Iterations	RE	
	SSA	BFSSA
100	6.07%	3.77%
500	5.12%	2.68%
800	3.79%	2.19%
1000	3.15%	1.05%

Table 9. Optimal solutions of BFSSA based chance-constrained model.

α	TP	TE	TL	Optimal solution
0.9	7496.4	130.4	279.8	$x^1_{111} = 0.1031, x^2_{111} = 0.9162, x^1_{112} = 6.4765, x^2_{112} = 52.1671$ $x^1_{121} = 41.0791, x^2_{121} = 0.0899, x^1_{122} = 26.5423, x^2_{122} = 10.5278$ $x^1_{211} = 51.5440, x^2_{211} = 0.4161, x^1_{212} = 8.3751, x^2_{212} = 19.5999$ $x^1_{221} = 15.2415, x^2_{221} = 42.0555, x^1_{222} = 1.3404, x^2_{222} = 2.3296$
0.8	7501.3	139.3	285.6	$x^1_{111} = 0.1223, x^2_{111} = 0.1818, x^1_{112} = 7.2447, x^2_{112} = 49.0569$ $x^1_{121} = 40.8141, x^2_{121} = 0.0297, x^1_{122} = 27.2197, x^2_{122} = 16.1324$ $x^1_{211} = 61.4594, x^2_{211} = 0.8766, x^1_{212} = 0.3778, x^2_{212} = 16.6182$ $x^1_{221} = 12.6451, x^2_{221} = 37.2562, x^1_{222} = 3.5182, x^2_{222} = 12.0499$
0.7	7502.7	148.2	291.4	$x^1_{111} = 0.0285, x^2_{111} = 2.1323, x^1_{112} = 9.3186, x^2_{112} = 51.6435$ $x^1_{121} = 40.1013, x^2_{121} = 0.0428, x^1_{122} = 27.1524, x^2_{122} = 13.2822$ $x^1_{211} = 62.3603, x^2_{211} = 0.1318, x^1_{212} = 0.6150, x^2_{212} = 16.8607$ $x^1_{221} = 13.7523, x^2_{221} = 35.7917, x^1_{222} = 2.7733, x^2_{222} = 15.4166$
0.6	7536.8	157.4	297.2	$x^1_{111} = 0.2073, x^2_{111} = 0.6100, x^1_{112} = 4.6265, x^2_{112} = 54.0461$ $x^1_{121} = 40.5918, x^2_{121} = 0.1559, x^1_{122} = 32.3754, x^2_{122} = 13.9890$ $x^1_{211} = 62.9584, x^2_{211} = 0.8924, x^1_{212} = 0.0947, x^2_{212} = 3.9369$ $x^1_{221} = 16.1495, x^2_{221} = 34.4356, x^1_{222} = 1.7984, x^2_{222} = 30.3360$

Table 10. Optimal solutions of chance-constrained model via SSA and BFSSA.

α	AL	TP	TE	TL
0.9	SSA	6739.4	124.6	264.4
	BFSSA	7496.4	130.4	279.8
0.8	SSA	6794.4	131.3	267.5
	BFSSA	7501.3	139.3	285.6
0.7	SSA	6846.0	138.2	270.6
	BFSSA	7502.7	148.2	291.4
0.6	SSA	6894.4	145.2	273.7
	BFSSA	7536.8	157.4	297.2

Table 11. Optimal solutions for optimization of EVM and CCM by BFSSA.

Weights		EVM		CCM	
w_1	w_2	$E[Z_1]$	$E[Z_2]$	$\overline{Z_1}$	$\overline{Z_2}$
0.8	0.2	7525.7	166.6453	7496.4	130.4405
0.5	0.5	7523.8	166.6520	7485.3	130.5131
0.3	0.7	7520.2	166.6520	7478.2	130.5203
0.1	0.9	7518.1	166.6523	7475.2	130.5321

Concerning the chance-constrained model, different confidence levels $\alpha = 0.9$, $\alpha = 0.8$, $\alpha = 0.7$and $\alpha = 0.6$were selected for the experiments and solved by SSA and BFSSA. As shown in Table 9, Table 10, similar to the expected value model, the results of BFSSA are better than SSA. Moreover, with the gradual decrease of the confidence level α, there appears to be a trend towards increasing net profit and carbon emissions. This occurs as a lower α reduces the reversal of certain uncertain parameter distributions, leading to a decrease in the objective function's outcome, hence causing both metrics to increase inversely.

To verify the effect of the linear weighted approach in optimizing search results, the two objective functions are recombined with varying weights. The outcome of the solution is presented below in Table 11. According to Table 11, it is evident that optimal solution varies with the parameter w_1, w_2under uncertainty and their outcomes are independent of one another. As w_1 gradually decreases and w_2 gradually increases, the objective function value changes accordingly. The linear weighted method mentioned in this manuscript obtains a unique solution when the weights are given, whereas the optimal solution derived from the neutrosophic linear programming (NLP) method mentioned in [43] is a large range of intervals, and the decision maker often needs to choose among these solutions, which increases the complexity of decision making. Therefore, the linear weighted method proposed in this paper better simplifies the decision-making process when each objective is relatively clear.

In addition, this paper will conduct numerical experiments to further explore the sensitivity of the chance-constrained scenario by assessing the effects of varying confidence levels on the models. The results, presented in Table 12, reveal that the objective functions do not increase with an increase in the confidence level.

Table 12. Sensitivity analysis of confidence level for objective functions.

α	$\overline{Z_1}$	$\overline{Z_2}$
0.95	7417.1	126.1
0.9	7468.8	130.4
0.8	7503.4	139.3
0.7	7525.7	148.3
0.6	7543.3	157.4

This phenomenon occurs because the model operates on a maximization principle, where expands the feasible domain of the problem, leading to a rise in the objective function as the confidence level reduces. This observation highlights that higher level of initiative prompt more cautious decision-making.

Finally, to further compare the algorithms, this manuscript was tested using the specific test function CEC2005, and the convergence curves are shown in Fig. 4, which clearly show that BFSSA performs much more favorably than SSA. BFSSA proves to be exceptionally effective in identifying optimal solutions, and it quickly adapts and accommodates changing problem conditions during the search process with good scalability and efficiency for optimization in high-dimensional search spaces, and also offers significant value in decision support systems.

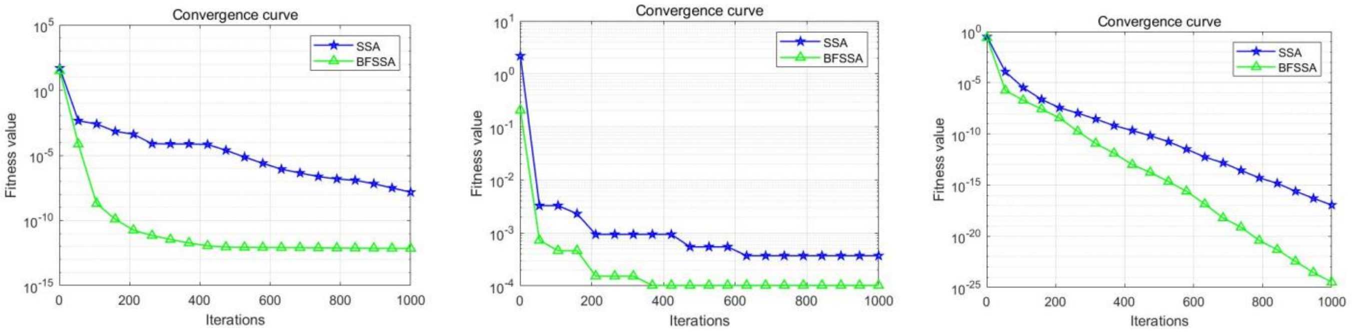

Fig. 4. Convergence curves for F5, F7, F13 in CEC2005.

8. Conclusion

This paper delves into a multi-objective transportation problem characterized by fixed charges and uncertainty. The study proposes a mathematical model designed to maximize net profit while minimizing carbon dioxide emissions during vehicle transportation, aiming to determine the best product transportation strategy. Subsequently, the basic model is expanded into two uncertain model variants. It then proves relevant theorems and derives corresponding forms through the application of the inverse uncertain distribution method, followed by employing a linear weighting method to address the parsing issue. Finally, the paper presents numerical examples to identify optimal solutions through the newly proposed sparrow optimization algorithm, enhanced by the integration of a butterfly search method. Through the method proposed in this paper, a complex multiple-objective transport problem can be transformed into a simplified single-objective transport problem, and assigning weights to each objective based on the subjective decision of the decision maker. The method is simple and intuitive and is suitable for multi-objective optimization problems. The proposed improved algorithm incorporates its unique individual-awareness ability into the sparrow algorithm, which enhances its global searching ability, which greatly facilitates our search for the optimal value and is more suitable for high-dimensional complex optimization problems. The results show that the improved algorithm is more conducive to finding the optimal solution and has better performance.

FCTP have a wide range of applications in areas such as logistics and supply chain management, urban transportation planning and transmission networks. This study has taken into account the uncertainties that may arise in the actual transportation process, introduced two new parameters of product sampling pass rate and carbon emissions, and developed an optimal product transportation strategy, which provides managers with an effective decision support tool to help them make transportation decisions based on profit-benefit and environmental-benefit considerations, and is very helpful to organizations or companies in solving economic and environmental problems. Based on the analysis of FCTP, it can help managers make more accurate and data-based decisions to optimize supply chain structure and operations. However, only profit and environmental impacts have been considered in this paper, and in the realities of transportation, where there are often more influencing factors and decision makers often need to consider a wider range of factors, such as delivery time, service quality, customer satisfaction and many other factors. In future research, the proposed methodology could be expanded upon and applied to address complex issues in nonlinear and imbalanced transportation challenges, among others. Developing an efficient loading and unloading strategy to significantly reduce time for specific goods presents a complex topic of study. Solutions to scheduling dilemmas, incorporating uncertainty, can be developed through a similar approach. Moreover, analyses could explore multi-stage transportation across varied settings, the timely delivery of multiple items, and the complex logistics of transporting hazardous materials under specific load limitations. In addition, delving into multi-objective optimization problems that consist of additional constraints will broaden the applicability of these solutions across various situations, thus offering more robust decision-making tools.

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