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# A MULTI-OBJECTIVE DYNAMIC NEUTROSOPHIC SOLID TRANSPORTATION MODEL UNDER IOT-DRIVEN UNCERTAINTY

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## Abstract

This research introduces an innovative Multi-objective Dynamic Neutrosophic Solid Transportation Model (MODNSTP) that integrates real-time uncertainty from IOT-enabled logistics systems. Transportation factors, including pricing, supply, and capacity, are articulated by Single-Valued Neutrosophic Numbers (SVNNs) to more effectively represent vagueness, indeterminacy and contradicting data. A neutrosophic ranking function is utilized to derive precise values for optimization. The model concurrently reduces cost, delay, and environmental effects over various time intervals. A revised Row-Column Reduction and MODI approach is suggested for allocation. Dynamic IoT inputs incessantly alter parameters over time. A numerical example demonstrates improved decision-making efficacy amid uncertainty. A comparative analysis of fuzzy and crisp models reveals the benefits of the proposed methodology. This methodology pertains to intelligent supply chains and the logistics of perishable goods. It provides a scalable solution for real-time, uncertainty-informed transportation planning.

**Keywords:** Neutrosophic sets; Solid Transportation Problem; IoT-driven Uncertainty; Multi-objective Optimization; Deneutrosophication; smart Logistics; Time-indexed Transportation

## 1. Introduction:

**2.** Transportation planning is essential in contemporary supply chain networks or optimising logistics costs, time, and resource efficiency. The classical solid transportation problem (STP) entails the movement of items from numerous origins to multiple destinations via various modes of transport, typically with deterministic or static characteristics. Real-world logistics environment is increasingly marked by real-time disruptions, unclear data, and uncertainty due to dynamic factors such as fluctuations in fuel costs, weather variations, and traffic congestion.

Conventional optimisation methods depend on precise or fuzzy models that do not adequately address profound uncertainties, including indeterminacy and inconsistent real-time sensor information. Neutrosophic set theory, which enhances fuzzy sets by incorporating degrees of truth, indeterminacy and falsehood, provides a more effective modelling framework for ambiguous or conflicting information.

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To our knowledge, no current study amalgamates neutrosophic uncertainty modelling, multi-objective optimisation, and IoT-based real-time input inside a dynamic solid transportation problem [27,26]. This research addresses the gap by presenting an innovative Multi-objective Dynamic Neutrosophic Solid Transportation Model (MODNSTP) that more truly represents the complexities of contemporary logistics. In our model:

- Single-Valued neutrosophic Numbers (SVNNs) are utilised to represent unpredictable transportation charges, supplies, and capacities amid sensor data ambiguity.
- A neutrosophic ranking function is utilized to extract precise values from uncertainty generated by IoT.
- A revised iteration of the Row-Columns Reduction and MODI approach is suggested to address the allocation problem effectively.
- Various objectives such as cost, delay and environmental impact are concurrently optimised throughout time-indexed decision intervals.

A detailed numerical example is provided to illustrate the viability and efficacy of the suggested paradigm. A comparative examination of fuzzy and crisp techniques confirms the superiority of the MODNSTP regarding adaptability, realism, and decision quality.

## 3. Literature Review:

Transport challenges are fundamental in operations research, particularly aimed at optimising the distribution of items from sources to destinations while adhering to cost, capacity, and supply-demand restrictions. Conventional models presume deterministic settings; yet, practical applications frequently entail uncertainty. Researchers have enhanced classical models by including fuzzy, type-2 fuzzy, neutrosophic, and, more recently, IoT-integrated models.

- **Fuzzy Set Theory in Transportation Models:**

The implementation of fuzzy set theory commenced with Zadeh (1965), who presented fuzzy sets to represent imprecise or ambiguous parameters in decision-making procedures [15]. This foundation motivated academics like Chanas and Kuchta (1998) to create a fuzzy integer transportation problem model to address ambiguity in supply, demand, and cost coefficients [2]. Fuzzy-based transportation modelling has progressed considerably. In order to enhance the veracity of parameter estimation and the resilience of solutions, Kamal et al. (2021) implemented type-2 trapezoidal fuzzy numbers in multi-objective transportation problems (MOTPs), improving realism in parameter estimation and solution resilience [7]. Das, Bera, and Maiti (2019) addressed solid transportation issues by modelling both input data uncertainty and environmental variability using type-2 fuzzy variables [3].

- **Neutrosophic and Fermatean Fuzzy Approaches**

The neutrosophic theory, which was introduced by Smarandache in 2004, is capable of modelling inconsistent or incomplete information by incorporating the concepts of truth, indeterminacy, and falsity, thereby extending fuzzy and intuitionistic fuzzy sets. Pratihar et al. (2019) enhanced the modelling of confusing logistical data by utilising neutrosophic environments to address transportation difficulties [9]. To improve the modelling process for the resolution of multi-objective transportation issues, Ali and Javaid (2025) introduced a Fermatean fuzzy programming method. This method allows the decision-maker to operate in the presence of a larger degree of uncertainty than traditional fuzzy approaches [1]. Singh et al. (2021) made a significant contribution by combining artificial neural networks (ANNs) with trapezoidal neutrosophic fuzzy analytic hierarchy process (AHP) to improve the precision of transit cost predictions in uncertain contexts [10]. Thamaraiselvi and Santhi (2016) introduced optimisation frameworks for real-world transportation that employ neutrophilic sets, demonstrating their superiority over traditional models in situations involving equivocal data [13].

- **Sustainable Supply Chains and Decision-Making Models**

Sustainability has become a core objective in logistics, prompting scholars to incorporate environmental metrics into supply chain optimisation. Yazdani et al. (2021) developed a multi-criteria decision-making model utilising interval-valued neutrosophic sets for the selection of sustainable suppliers. Their methodology effectively integrated conflicting sustainability metrics [14]. Szmelter-Jarosz et al. (2021) presented a neutrosophic fuzzy optimisation framework aimed at enhancing sustainable closed-loop supply chains, particularly relevant during disruptive events such as COVID-19, addressing the complexities of modern supply networks [12].

- **IoT Integration in Transportation Optimization**

Decisions in logistics now incorporate real-time data dynamics, made possible by the proliferation of the Internet of Things (IoT). Taking into account hardware capabilities, adaptability, and scalability, Ilieva and Yankova (2022) described the selection of IoT systems as a fuzzy multi-criteria decision-making dilemma [5]. To optimise urban transport networks on the fly, Fatorachian et al. (2025) proposed a smart city logistics model [4] that makes use of cybernetic feedback mechanisms and predictive analytics made possible by the Internet of Things. In order to make supply chain finance more resilient, Nozari, Nassar, and Szmelter-Jarosz (2025) created a fuzzy multi-objective optimisation model that uses blockchain and the internet of things. Aligning environmental goals with real-time decision-making systems, Javanpour et al. (2025) presented a multi-modal transportation model that minimises operational costs and carbon emissions through the use of a sustainability-oriented routing system [6].

**Research Gap:** Obstacles continue to exist, despite the integration of IoT and fuzzy and neuromorphic methodologies:

- Most models consider uncertainty as static instead of dynamically changing it with real-time input.
- Limited frameworks integrate neutrosophic logic and the Internet of Things for decision-making amidst upheaval.
- There is a paucity of research on complex transportation issues that encompass many modes, objectives, and significant uncertainty concurrently.

The study emphasises the necessity for a multi-objective, dynamic optimisation framework that incorporates IoT-derived data with neutrosophic logic and sophisticated fuzzy modelling approaches to enhance the resilience, cost-efficiency, and sustainability of transportation systems.

## 4. Preliminaries:

The fundamental mathematical principles required to model transportation issues within neutrophilic and dynamic uncertainty contexts are presented in this section. In order to process real-time data from IoT sensors, the framework employs Single-valued Neutrosophic Sets (SVNS) and incorporates Deneutrosophication techniques and ranking algorithms.

### 4.1. Single-Valued Neutrosophic Sets (SVNSs)

$X$ the universe of discourse, a single-valued neutrosophic Set (SVNS) $A$ is defined as: $A = \{\langle x, T_A(x), I_A(x), F_A(x)\rangle | x \in X\}$

where:

- $T_A(x), I_A(x), F_A(x) \in [0,1]$
- $0 \leq T_A(x), +I_A(x) + F_A(x) \leq 3$

Each element is associated with $T$ degree of truth I degree of indeterminacy and $F$ degree of falsity

### 4.2. Deneutrosophication Function:

To make SVNN data (costs, supplies, capacities) usable in classical algorithms (e.g., MODI, row-column reduction), they must be converted into crisp values. This is achieved via a deneutrosophication function.

$$D(A) = \frac{T + (1 - F) - I}{2}$$

This function reconciles truth, falsity, and ambiguity to derive a useable scalar value from an SVNN input.

### 4.3. Neutrosophic Ranking Function:

To compare, emphasise, or allocate among alternatives with neutrosophic values, we employ a ranking function that transforms a Single-Valued Neutrosophic Number (SVNN) into a precise scalar value. This work employs improved Geometric Mean-based Ranking Function, since it effectively nonlinearly penalises inaccuracies and rewards greater confidence in real-time decision-making.

$$R_{GM}(A) = \sqrt{T.(1 - F)} - I$$

**5. Methodology:** The suggested methodology tackles the Multi-Objective Dynamic Neutrosophic Solid Transportation Problem (MODNSTP) through the use of uncertainty modelling, IoT-driven dynamic inputs, and multi-objective optimisation. The entire procedure is detailed below and illustrated in Fig. 1.

### A. Problem Definition and Data Acquisition

Data on transportation costs, emissions, and time delays are gathered via an IoT-enabled logistics network. Due of the intrinsic uncertainty in sensor-generated data, the input parameters are expressed as Single-Valued Neutrosophic Numbers (SVNNs).

### B. Model Formulation

A multi-objective optimisation model is developed, integrating three competing objectives:

- Reduction of transportation expenses,
- Reduction of emission levels, and
- Reduction of delivery time.

The objectives are consolidated into a singular composite cost function utilising user-specified weight $w_1, w_2, w_3 \in [0,1]$, with $w_1 + w_2 + w_3 = 1$,

$$Total\ Cost_{ijk}(t) = w_1 . \hat{C}_{ijk}(t) + w_2 . E_{jk}(t) + w_3 . \frac{1}{t}$$

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### C. Deneutrosophication

The parameters based on SVNN are transformed into accurate scores using a standard deneutrosophication algorithm. This ensures compatibility with conventional optimisation methods.

### D. Initial Feasible Solution

The initial feasible allocation that satisfies all supply and demand restrictions is generated using the Row-Column Reduction Method.

### E. Optimization Using MODI

Subsequently, the precise transportation matrix is subjected to the Modified Distribution Method (MODI) in order to continuously optimise the allocation until perfection is achieved.

### F. Sensitivity Analysis

To assess the model's adaptability to various strategic objectives, many weight combinations are examined:

- Cost-priority scenario ($w_1 = 0.5$ )
- Emission-priority scenario ($w_2 = 0.8$ )
- Time-priority scenario ($w_3 = 0.8$ )

The effect of each configuration on overall transportation costs is examined to uncover trade-offs between competing objectives.

### G. Managerial Insight

The final results furnish decision-makers with practical insights, allowing them to adaptively transition among cost-efficiency, environmental sustainability, and service-level optimisation in accordance with organisational priorities or external restrictions.

## 6. Problem Formulation:

We consider a dynamic solid transportation model with:

- $m$ Origins $O_i$
- $n$ Destinations $D_j$
- $l$ conveyance modes $E_k$
- Time horizon $t \in T = \{1,2, \dots, \tau\}$

Transportation costs, supply, demand, and capacity are represented as Single-Valued Neutrosophic Numbers (SVNN) derived from IoT devices. The objective is to ascertain the ideal quantity $x_{ijk}(t)$ to be conveyed from origin $i$ to destination $j$ through conveyance method $k$ at time t, while minimizing overall transportation costs and adhering to system restrictions.

### 6.1. Parameters and Notations:

**Table.1 Symbols and Meanings**

| SYMBOL | MEANING |
|---|---|
| $\boldsymbol{C_{ijk}(t)}$ | **Neutrosophic transportation cost from $O_i$ to $D_j$ via $E_k$ at time $t$ (SVNN)** |

| | |
|---|---|
| $x_{ijk}(t)$ | **Quantity shipped from $O_i$ to $D_j$ via $E_k$ at time $t$ (Decision variable)** |
| $S_i(t)$ | **Supply at origin $O_i$ at time $t$ (SVNN)** |
| $D_j(t)$ | **Demand at destination $D_j$ at time $t$ (SVNN)** |
| $Cap_{ijk}(t)$ | **Capacity of conveyance mode $E_k$ for route $(i,j)$ at time t (SVNN)** |
| $\hat{C}_{ijk}(t)$ | **Deneutrosophicated cost using geometric ranking function** |

All SVNN inputs are converted to crisp values via:

$$\hat{C}_{ijk}(t) = \sqrt{T_{ijk}(t).\left(1 - F_{ijk}(t)\right)} - I_{ijk}(t)$$

### 6.2. Objective Function:

Consider the multi-objective cost function merging total transportation cost, environmental penalty, time-indexed preference

Let weights $w_1, w_2, w_3 \in [0,1]$, with $w_1 + w_2 + w_3 = 1$, then:

$$Minimize\ Z = \sum_{t=1}^{\tau}\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{l}\left[w_1.\hat{C}_{ijk}(t) + w_2.E_{jk}(t) + w_3.\frac{1}{t}\right].x_{ijk}(t)$$

where $E_{jk}(t)$ is the environmental impact coefficient of mode $E_k$ to $D_j$ at time $t$ (can be predefined or calculated).

### 6.3. Constraints:

**a) Supply Constraint (per origin per time):**

$$\sum_{j=1}^{n}\sum_{k=1}^{l} x_{ijk}(t) \le \hat{S}_i(t), \forall i, t$$

**b) Demand Constraint**

$$\sum_{i=1}^{m}\sum_{k=1}^{l} x_{ijk}(t) \le \hat{D}_i(t), \forall i, t$$

**c) Conveyance Capacity Constraint (per route and time):**

$$x_{ijk}(t) \le \widehat{Cap}_i(t), \forall i, j, k, t$$

**d) Non-negativity:**

$$x_{ijk}(t) \le 0, \forall i, j, k, t$$

**e) Time Consistency Constraint**

$$x_{ijk}(t) \le x_{ijk}(t+1) + \delta, \forall i, j, k, t$$

## 7. Proposed Algorithm:

This section presents the computational framework for addressing the Multi-Objective Dynamic Neutrosophic Solid Transportation Problem (MODNSTP) amid IoT-induced uncertainty. The methodology incorporates neutrosophic deneutrosophication, temporally indexed cost adjustments for effective and instantaneous optimisation.

### 7.1. Step-by-Step Algorithm:

**Step 1: Data Acquisition from IoT Sources**

Collect real-time logistics parameters where all values are in SVNN form

$$C_{ijk}(t), S_i(t), D_j(t), Cap_{ijk}(t)$$

$$A = (T, I, F)$$

**Step 2: Deneutrosophication using Geometric mean**

Convert all neutrosophic data into crisp equivalents using

$$\hat{C}_{ijk}(t) = \left(\sqrt{T_{ijk}(t).\left(1 - F_{ijk}(t)\right)} - I_{ijk}(t)\right) \times 10$$

Similarly apply to $S_i(t), D_j(t), Cap_{ijk}(t)$

**Step 3: Time-Based Cost Matrix Construction**

For each time step $t = 1$ to $\tau$, Construct the crisp cost matrix $\hat{C}_{ijk}(t)$ also weights $w_1, w_2, w_3$ may be used to combine cost, emission, and time priority:

$$Total\ Cost_{ijk}(t) = w_1.\hat{C}_{ijk}(t) + w_2.E_{jk}(t) + w_3.\frac{1}{t}$$

**Step 4: Row-Column Reduction**

**Perform the row-wise and column-wise reductions:**

**Row reduction:** $R_{ijk} = \hat{C}_{ijk}(t) - \min_{j,k} \hat{C}_{ijk}(t)$

**Column Reduction:** $CO_{ijk} = \hat{C}_{ijk}(t) - \min_{i,k} \hat{C}_{ijk}(t)\ for\ each\ fixed\ j$

Also, use the minimum sum of $R + CO$ to select allocation cell

**Step 5: Feasible Allocation Based on Supply, Demand and Capacity**

At each allocation step perform

$$x_{ijk}(t) = min\{\hat{S}_i(t), \hat{D}_j(t), \widehat{Cap}_{ijk}(t)\}$$

And remove exhausted rows/columns/conveyances.

**Step 6: Optimality test using MODI (Modified Distribution Method)**

Compute opportunity costs $\Delta_{ijk}$ using MODI u-v method, if all $\Delta_{ijk} \geq 0$, current solution is optimal. Otherwise, perform loop-based reallocation.

**Step 7: Repeat for all time steps**

For $t = 1$ to $\tau$, repeat steps 3-6, maintain a rolling optimization window if data changes dynamically.

**Step 8: Total Objective Value Computation**

Compute total cost over $\tau$ time periods:

$$Z = \sum_{t=1}^{\tau} \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{l} Total\ Cost_{ijk}(t).x_{ijk}(t)$$

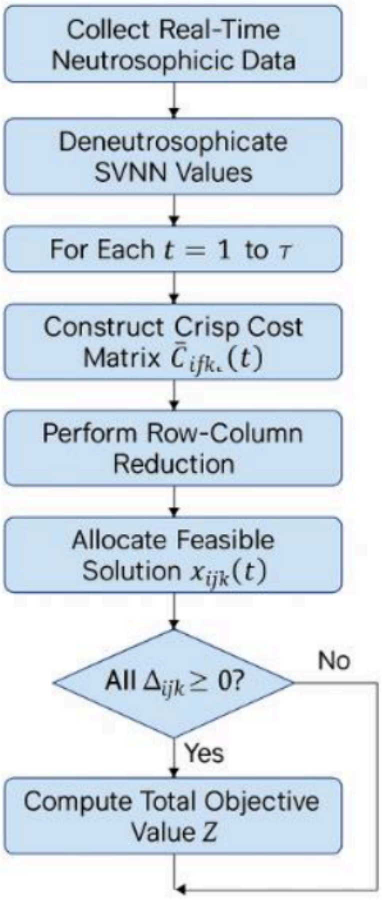

**Figure 1. Flowchart of Proposed Algorithm**

## 8. Formulation of the Problem:

In the era of industry 4.0 and intelligent logistics, supply chain networks increasingly depend on Smart IoT-connected infrastructure to facilitate real-time decision-making. These systems comprise networked sensors, GPS-Equipped delivery fleets, RFID-tagged stocks, and cloud-

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based management platforms. Although IoT technologies enhance visibility and responsiveness, they concurrently present multi-faceted concerns arising from inconsistent sensor readings, delayed or absent data packets, and external interruptions such as weather, congestion, and power instability. Contradictory indications from several data sources.

A national logistics company is enhancing its intelligent distribution system by using IoT-connected systems across its supply chain. The network consists of three eco-certified fulfilment centres: Chennai Eco Hub $(G_1)$, Bengaluru Green Dispatch Zone $(G_2)$, and Pune IoT-Managed Depot $(G_3)$, which cater to three primary urban consumer area: Mumbai Retail Cluster $(D_1)$, Hyderabad Metro Catchment $(D_2)$, and Delhi Urban market $(D_3)$. The company employs three transportation modes for sustainable and efficient delivery: electric vehicles $(E_1)$, rail cargo $(E_2)$, and hybrid air freights $(E_3)$. These intelligent systems gather real-inventories and telematics platforms to facilitate dynamic planning decisions. Nonetheless, because of uncertainties including sensor malfunctions, latency, conflicting data inputs, and fluctuations in availability, the transportation costs, supply levels, demand volumes, and carrier capacities are represented using Single-Valued Neutrosophic Numbers (SVNNs). Each SVNN quantifies the levels of Truth $(T)$, indeterminacy $(I)$, and falsehood $(F)$ to encapsulate ambiguity and partial belief in IoT-generated information.

This study integrates two dynamic modifiers into the transportation cost model to accurately represent real-world logistics under sustainability mandates and delivery urgency: i) a real-time emission impact factor obtained from IoT sensors installed in vehicles, and ii) a time-priority function indicating service urgency at different temporal stages. These modifiers provide more flexible and ecologically-conscious routing selections.

The purpose is to establish an optimal solid transportation strategy that allocates goods from fulfilment centres to consumer areas through available transport methods, while minimising overall costs and concurrently adhering to neutrosophic constraints regarding supply, demand, and vehicle availability in an uncertain, data-driven context.

Below is the realistic neutrosophic numerical case table and the Neutrosophic capacity values for each conveyance modes $E_1, E_2, E_3$ are given by $(0.99,0.15,0.14), (0.99,0.15,0.15), (0.99,0.13,0.12)$ and the deneutrosophic values are given by $(0.7727, 0.7673, 0.8133)$ we have $E_1 = 7, E_2 = 6, E_3 = 8$ after approximation and converting into crisp value by multiplying each of $E_1, E_2, E_3$ by 10.

**Step 1:** Data Acquisition from IoT sources

**Table 1. Cost Matrix**

| ORIGIN | DESTINATIONS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $D_1$ | | | $D_2$ | | | $D_3$ | | | |
| | $E_1$ | $E_2$ | $E_3$ | $E_1$ | $E_2$ | $E_3$ | $E_1$ | $E_2$ | $E_3$ | SUPPLY |
| *Chennai Eco Hub* $(G_1)$ | (0.5,0.1,0.2 | (0.6,0.2,0.3 | (0.9,0.1,0.4 | (0.4,0.1,0.3 | (0.5,0.3,0.2 | (0.9,0.2,0.3 | (0.4,0.2,0.3 | (0.5,0.2,0.4 | (0.8,0.3,0.2 | (0.85,0.1,0.2 |
| *Bengaluru Gree Dispatch* | (0.6,0.1,0.3 | (0.5,0.2,0.4 | (0.8,0.3,0.3 | (0.3,0.2,0.2 | (0.6,0.2,0.3 | (0.8,0.1,0.2 | (0.3,0.1,0.2 | (0.5,0.2,0.3 | (0.9,0.3,0.2 | (0.8,0.2,0.2) |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| *Zone* $(G_2)$ | | | | | | | | | | |
| *Pune IoT* − *Managed Depot* $(G_3)$, | (0.6,0.1,0.2 | (0.4,0.2,0.4 | (0.8,0.3,0.5 | (0.5,0.2,0.3 | (0.5,0.3,0.3 | (0.7,0.2,0.4 | (0.2,0.2,0.4 | (0.6,0.1,0.3 | (0.9,0.3,0.2 | (0.9,0.1,0.1) |
| DEMAND | (0.9,0.1,0.1) | | | (0.85,0.2,0.1) | | | (0.8,0.2,0.2) | | | |

## Table 2. Emission Matrix

| ORIGIN | DESTINATIONS | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $D_1$ | | | $D_2$ | | | $D_3$ | | |
| | $E_1$ | $E_2$ | $E_3$ | $E_1$ | $E_2$ | $E_3$ | $E_1$ | $E_2$ | $E_3$ |
| *Chennai Eco Hub* $(G_1)$ | (0.55, 0.01, 0.44) | (0.97, 0.02, 0.01) | (1, 0.01, 0) | (0.51, 0.01, 0.48) | (1, 0.03, 0) | (1, 0.04, 0) | (0.54, 0.05, 0.41) | (1, 0.06, 0) | (1, 0.02, 0) |
| *Bengaluru Green Dispatch Zone* $(G_2)$ | (0.59, 0.06, 0.35) | (1.0, 0.01, 0) | (1, 0.04, 0) | (0.52, 0.07, 0.41) | (1, 0.09, 0) | (1, 0.07, 0) | (0.57, 0.01, 0.42) | (1, 0.06, 0) | (1, 0.07, 0) |
| *Pune IoT* − *Managed Depot* $(G_3)$, | (0.53, 0.04, 0.43) | (0.98, 0.0, 0.02) | (1, 0.03, 0) | (0.59, 0.05, 0.36) | (1, 0.09, 0) | (1, 0.03, 0) | (0.52, 0.07, 0.41) | (1, 0.07, 0) | (1, 0.01, 0) |

## Table 3. Time Matrix

| ORIGIN | DESTINATIONS | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $D_1$ | | | $D_2$ | | | $D_3$ | | |
| | $E_1$ | $E_2$ | $E_3$ | $E_1$ | $E_2$ | $E_3$ | $E_1$ | $E_2$ | $E_3$ |
| *Chennai Eco Hub* $(G_1)$ | 48 | 36 | 12 | 48 | 36 | 12 | 48 | 36 | 12 |
| *Bengaluru Green Dispatch Zone* $(G_2)$ | 48 | 36 | 12 | 48 | 36 | 12 | 48 | 36 | 12 |
| *Pune IoT* − *Managed Depot* $(G_3)$, | 48 | 36 | 12 | 48 | 36 | 12 | 48 | 36 | 12 |

### Step 2: Deneutrosophication using Geometric mean

## Table. 4 Deneutrosophication of Cost Matrix

| ORIGIN | DESTINATIONS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $D_1$ | | | $D_2$ | | | $D_3$ | | | |
| | $E_1$ | $E_2$ | $E_3$ | $E_1$ | $E_2$ | $E_3$ | $E_1$ | $E_2$ | $E_3$ | SUPPLY |
| *Chennai Eco Hub* $(G_1)$ | 5.3 | 4.5 | 6.3 | 4.3 | 3.3 | 5.9 | 3.3 | 3.5 | 5 | 7.2 |
| *Bengaluru Green* | 5.5 | 3.5 | 4.5 | 2.9 | 4.5 | 7 | 3.9 | 3.9 | 5.5 | 6 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Dispatch Zone ($G_2$) | | | | | | | | | | |
| Pune IoT − Managed Depot ($G_3$), | 3.9 | 2.9 | 3.3 | 3.9 | 2.9 | 4.5 | 1.5 | 5.5 | 5.5 | 8 |
| DEMAND | | | | | | | | | | |

**Table. 5 Deneutrosophication of Emission Matrix**

| ORIGIN | DESTINATIONS | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $D_1$ | | | $D_2$ | | | $D_3$ | | |
| | $E_1$ | $E_2$ | $E_3$ | $E_1$ | $E_2$ | $E_3$ | $E_1$ | $E_2$ | $E_3$ |
| Chennai Eco Hub ($G_1$) | 5.4 | 9.6 | 9.9 | 5 | 9.7 | 9.6 | 6.7 | 9.4 | 9.8 |
| Bengaluru Green Dispatch Zone ($G_2$) | 5.6 | 939 | 9.6 | 4.8 | 9.1 | 9.3 | 5.6 | 9.4 | 9.3 |
| Pune IoT − Managed Depot ($G_3$), | 5.1 | 9.8 | 9.7 | 5.6 | 9.1 | 9.7 | 4.8 | 9.3 | 9.9 |

**Table. 6 Deneutrosophication of Time Matrix**

| ORIGIN | DESTINATIONS | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $D_1$ | | | $D_2$ | | | $D_3$ | | |
| | $E_1$ | $E_2$ | $E_3$ | $E_1$ | $E_2$ | $E_3$ | $E_1$ | $E_2$ | $E_3$ |
| Chennai Eco Hub ($G_1$) | 0.2 | 0.3 | 0.8 | 0.2 | 0.3 | 0.8 | 0.2 | 0.3 | 0.8 |
| Bengaluru Green Dispatch Zone ($G_2$) | 0.2 | 0.3 | 0.8 | 0.2 | 0.3 | 0.8 | 0.2 | 0.3 | 0.8 |
| Pune IoT − Managed Depot ($G_3$), | 0.2 | 0.3 | 0.8 | 0.2 | 0.3 | 0.8 | 0.2 | 0.3 | 0.8 |

**Step 3:** Construction of crisp cost matrix $\hat{C}_{ijk}(t)$ using the below formula which combines cost, emission and weights

$$Time - Cost - Emission_{ijk}(t) = w_1.\hat{C}_{ijk}(t) + w_2.\hat{E}_{jk}(t) + w_3.\frac{1}{t}$$

We consider the weights to be $w_1 = 0.5, w_2 = 0.3, w_3 = 0.2$ and here we assume time priority weight as $t = 1$. The below table gives the time-cost matrix

**Table. 7 Final Cost Matrix**

| ORIGIN | DESTINATIONS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $D_1$ | | | $D_2$ | | | $D_3$ | | | |
| | $E_1$ | $E_2$ | $E_3$ | $E_1$ | $E_2$ | $E_3$ | $E_1$ | $E_2$ | $E_3$ | SUPPLY |
| $Chennai\ Eco\ Hub\ (G_1)$ | 4.31 | 5.19 | 6.28 | 3.69 | 4.62 | 5.99 | 3.7 | 4.63 | 5.6 | 7 |
| $Bengaluru\ Green\ Dispatch\ Zone\ (G_2)$ | 4.47 | 4.78 | 5.29 | 2.93 | 5.04 | 6.45 | 3.67 | 4.83 | 5.7 | 6 |
| $Pune\ IoT - Managed\ Depot\ (G_3),$ | 3.52 | 4.45 | 4.45 | 3.67 | 4.24 | 5.32 | 2.23 | 5.6 | 5.88 | 8 |
| DEMAND | 8 | | | 7 | | | 6 | | | |

**Step 4: Row Column reduction**

**Table. 8 Row Column reduction**

| ORIGIN | DESTINATIONS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $D_1$ | | | $D_2$ | | | $D_3$ | | | |
| | $E_1$ | $E_2$ | $E_3$ | $E_1$ | $E_2$ | $E_3$ | $E_1$ | $E_2$ | $E_3$ | SUPPLY |
| $Chennai\ Eco\ Hub\ (G_1)$ | $4.31_{0.79}^{0.62}$ | $5.19_{1.67}^{1.5}$ | $6.28_{2.76}^{2.59}$ | $3.69_{0.76}^{0}$ | $4.62_{1.69}^{0.93}$ | $5.99_{3.06}^{2.3}$ | $3.7_{1.47}^{0.01}$ | $4.63_{2.4}^{0.94}$ | $5.6_{3.37}^{1.91}$ | 7 |
| $Bengaluru\ Green\ Dispatch\ Zone\ (G_2)$ | $4.47_{0.95}^{1.54}$ | $4.78_{1.26}^{1.85}$ | $5.29_{1.77}^{2.36}$ | $2.93_{0}^{0}$ | $5.04_{2.11}^{2.11}$ | $6.45_{3.52}^{3.52}$ | $3.67_{1.44}^{0.74}$ | $4.83_{2.6}^{1.9}$ | $5.7_{3.47}^{2.77}$ | 6 |
| $Pune\ IoT - Managed\ Depot\ (G_3),$ | $3.52_{0}^{1.29}$ | $4.45_{0.93}^{2.22}$ | $4.78_{1.26}^{2.55}$ | $3.67_{0.74}^{1.44}$ | $4.24_{1.31}^{2.01}$ | $5.32_{2.39}^{3.09}$ | $2.23_{0}^{0}$ | $5.6_{3.37}^{3.37}$ | $5.88_{3.65}^{3.65}$ | 8 |
| DEMAND | 8 | | | 7 | | | 6 | | | |

**Step 5: Feasible Allocation Based on Supply, Demand and Capacity**

**Table. 9 Feasible allocations**

| ORIGIN | DESTINATIONS | | | | | |
|---|---|---|---|---|---|---|
| | $D_1$ | | $D_2$ | | $D_3$ | |
| | $E_1$ | $E_3$ | $E_2$ | $E_3$ | $E_1$ | |
| $Chennai\ Eco\ Hub\ (G_1)$ | 4.31 $\boxed{\varepsilon}$ | 6.28 | 4.62 $\boxed{6}$ | 5.99 $\boxed{1}$ | 3.7 | $u_1 = 0.79$ |
| $Bengaluru\ Green\ Dispatch\ Zone\ (G_2)$ | 4.47 | 5.29 $\boxed{6}$ | 5.04 | 6.45 | 3.67 | $u_2 = 0.51$ |
| $Pune\ IoT - Managed\ Depot\ (G_3),$ | 3. 52 $\boxed{1}$ | 4.78 $\boxed{1}$ | 4.24 | 5.32 | 2.23 $\boxed{6}$ | $u_3 = 0$ |
| | $v_1 = 3.52$ | $v_2 = 4.78$ | $v_3 = 3.83$ | $v_4 = 5.2$ | $v_5 = 2.23$ | |

**Step 6: Optimality test using MODI (Modified Distribution Method)**

$C_{ij} = u_i + v_j$ $\qquad$ $d_{ij} = C_{ij} - \left(U_i + V_j\right)$

$4.31 - 3.52 = u_1$

$0.79 = u_1$

Total transportation cost using the final cost matrix and allocated values.

$$\text{Total cost} = 6 \times 4.62 + 1 \times 5.99 + 6 \times 5.29 + 1 \times 3.52 + 1 \times 4.78 + 6 \times 2.23 + 4.61 \times \varepsilon$$

$$= 27.72 + 5.99 + 31.74 + 3.52 + 4.78 + 13.38 = 87.13$$

$4.31 = u_1 + 3.52$ $\qquad$ $All\ d_{ij} \geq 0$

## 9. Sensitivity Analysis:

To examine the effects of fluctuations in cost weights, emission impact, and priority urgency on the overall transportation expenditure. This emphasises the adaptability and resilience of the proposed methodology in practical logistics.

Here we vary the weight parameters in the total cost function:

**Table. 10 Varied weight parameters**

| Case | $w_1{:}\,Cost$ | $w_2{:}\,Emission$ | $w_3{:}\,Time\ Priority$ | $Total\ Cost$ |
|---|---|---|---|---|
| Base Case | 0.5 | 0.3 | 0.2 | 87.13 |
| Case A | 0.1 | 0.8 | 0.1 | 143.22 |
| Case B | 0.1 | 0.1 | 0.8 | 32.18 |

### 9.1. Interpretation:

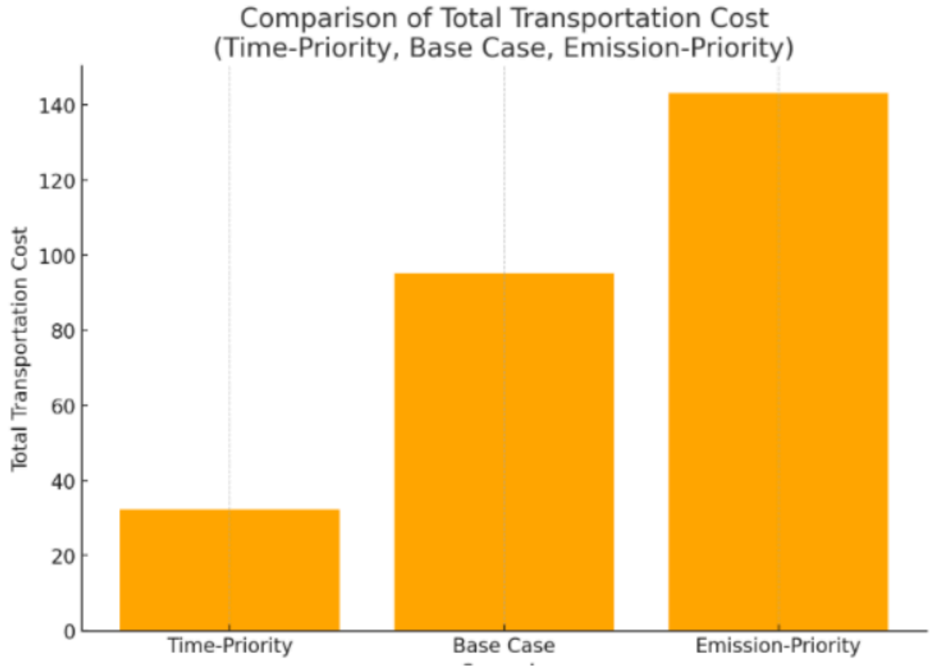
- **Time-Priority Case** ($w_3 = 0.8$): The minimal expense was generated, indicating that expedited routes may be underutilised or exhibit greater efficacy within this specific dataset. in the direction of more environmentally sustainable alternatives, despite their higher costs.
- **Emission-Priority Case** ($w_2 = 0.8$) resulted in the highest overall expenditure, illustrating a substantial trade-off between economic efficacy and ecological sustainability.
- The model's neutrality under standard preferences was confirmed by the basic scenario the basic scenario ($w_1 = 0.5$) which maintained an equitable cost structure across all modalities.

The sensitivity analysis verifies that the MODNSTP model can adapt to changing strategic objectives, providing decision-makers the freedom to prioritise cost, sustainability, or service-level requirements based on real-time business situations or regulatory mandates.

### 9.2. Comparison of Total costs:

| **Scenario** | **Total cost** |
|---|---|
| **Base Case** | **87.13** |
| **Case A** | **143.22** |
| **Case B** | **32.18** |

**Comparison Chart**



**10. Conclusion:** This study presents a Multi-Objective Dynamic Neutrosophic Solid Transportation Problem (MODNSTP) that integrates IoT-induced uncertainty using Single-Valued Neutrosophic Numbers (SVNNs). The approach offers a practical and adaptable basis for modern, data-centric logistics systems by simultaneously decreasing transportation expenses, emissions, and delivery urgency. The model employs a modified Row-Column Reduction and MODI approach subsequent to deneutrosophication to achieve time-indexed, feasible allocations. The sensitivity analysis across various weight scenarios demonstrated the model's flexibility. The time-priority scenario produced the lowest total cost, whereas the emission-priority scenario incurred higher expenses, so confirming the model's flexibility in accommodating shifting objectives. Whereas classical transportation models prioritise cost minimisation, the MODNSTP incorporates multi-dimensional trade-offs. Optimality is described as a strategic equilibrium among economic, environmental, and service-level objectives. The sensitivity results confirm the model's practical flexibility to various supply chain priorities.

**Future Scope:** Future endeavours may expand this framework by incorporating extensive real-time data, integrating AI predictive tools, and implementing industry-specific customisations to improve decision-making among uncertainty**.**

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