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Three-dimensional Euclidian Distance to Neutrosophic Number for Travelling Salesman Problem

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Abstract

The main idea in this paper is to study the application of the novel greedy Dhouib-Matrix-TSP1 (DM-TSP1) method to solve the Travel Salesman Problem with simple neutrosophic numbers. Here, the Euclidian distance is used to convert the neutrosophic number to crisp values, it is considered that the neutrosophic number as a three-dimensional coordinate. DM-TSP1 is a constructive method and requires just (n-1) iterations to generate to create a solution (where n is the number of nodes). Computational results on a case study developed in the literature prove that the proposed DM-TSP1 heuristic can create better solution than the Genetic Algorithm with a fitness improvement of 92.68%.

Keywords: Neutrosophic Number, Artificial Intelligence, Operations Research, Heuristic, Dhouib-Matrix-TSP1, Euclidian Distance.

1. Introduction

In daily life, we frequently encounter situations that are incomplete, unclear, and ambiguous. To address such challenges, mathematician Prof. Lotfi A. Zadeh introduced the concept of fuzzy sets in 1965 [1]. Fuzzy sets effectively manage situations involving uncertainty by allowing partial membership values; however, they do not account for non-membership explicitly. To address this limitation, Atanassov extended fuzzy set theory in 1983 by introducing intuitionistic fuzzy sets [2], which incorporate both membership and non-membership values. Later, in 1995, Smarandache further generalized this concept with neutrosophic sets, which added a third component to capture indeterminacy, thereby allowing for the representation of three membership values: truth (T), indeterminacy (I), and falsity (F) [3]. Neutrosophic sets thus provide a more comprehensive framework for modelling uncertainty and ambiguity in various complex real-world applications.

The Travelling Salesman Problem (TSP) is among the most widely researched optimization problems in operations research and theoretical computer science. Classified as NP-hard, TSP poses significant computational challenges, as finding an optimal solution in polynomial time is infeasible for large instances. Initially introduced in the 1930s, TSP gained substantial attention after the 1950s due to its importance in both theoretical and applied research [1, 2]. The problem is conventionally framed as follows: given a list of cities and the distances between each city pair, the objective is to determine the shortest possible route that visits each city exactly once and returns to the starting point. TSP has extensive applications in logistics, transportation, circuit board design, and DNA sequencing.

The study of optimization problems is crucial in engineering and computational sciences, as finding optimal solutions under various constraints is fundamental to improving system performance, efficiency, and resource utilization. Consequently, numerous research studies have focused on optimization, resulting in a wealth of published literature that explores various methods and algorithms for achieving optimal solutions in diverse applications [3,4,5,6,7,8,9,10,11,12,13]. These studies contribute to solving complex, real-world problems across fields such as logistics, network design, energy management, and machine learning, where optimization plays a pivotal role.

Over the years, numerous researchers have explored TSP and proposed various solutions. For instance, Raut et al. [14] used a random-key genetic algorithm to evaluate the shortest path, while Chiung Moon et al. [15] applied an efficient genetic algorithm. In-Chan Choi et al. [16] tackled the asymmetric TSP with a genetic algorithm employing a mixed-region search, and Zakir H. Ahmed et al. [17] developed a genetic algorithm with a sequential constructive crossover operator. Jayanta Majumdar et al. [18] extended genetic algorithms to solve the asymmetric TSP with imprecise travel times, and Sangit Chatterjee et al. [19] utilized genetic algorithms for TSP solutions. Additionally, Ch-Ch Chou et al. [20] used triangular fuzzy numbers and canonical representations to model multiplication operations in TSP, furthering the field's understanding of how to handle uncertainty in routing problems.

The concept of three-dimensional Euclidean distance (3D-ED) provides a spatially enriched approach to measuring distances, essential in applications that span three dimensions. Unlike two-dimensional Euclidean distance, 3D-ED accounts for variations along all three axes, offering a more accurate representation of real-world distances, especially where the third dimension is critical, such as in air or maritime navigation, satellite positioning, and high-rise urban routing. Integrating 3D-ED into TSP allows for a more realistic representation of distances in practical applications. While 3D-ED has been applied in various fields, its integration into TSP, particularly under conditions of uncertainty, is still a developing area of research.

This paper introduces an innovative approach that combines 3D-ED with neutrosophic numbers to tackle the TSP under uncertain conditions. The proposed model enhances the classical TSP by applying neutrosophic numbers to the 3D-ED calculations, allowing for uncertain distance values while preserving the spatial accuracy afforded by three-dimensional modelling. This hybrid approach brings a novel perspective to TSP research, focusing on not only optimizing routes but also managing the ambiguity inherent in real-world measurements.

The motivation behind this study is twofold. First, there is a need to enhance TSP formulations by incorporating three-dimensional spatial relationships and indeterminate factors affecting distances. Traditional TSP approaches typically rely on exact distance values, which are often approximations or averages with varying degrees of confidence in real-world settings. By introducing neutrosophic numbers, this model allows distances to represent intervals of possible values with associated degrees of certainty, better capturing real-world complexities. Second, existing approaches that account for uncertainty in TSP commonly use probabilistic or fuzzy models, which may not fully represent the spectrum of indeterminacy found in scenarios where information is incomplete or only partially available. Neutrosophic numbers help bridge this gap, providing a broader framework to represent uncertainty through three components (truth, indeterminacy and falsity).

The remaining of the paper is organized as follows: Section 2 presents preliminary, covering various definitions related to neutrosophic sets. Section 3 presents the greedy DM-TSP1 method and Section 4 presents a numerical example with empirical analysis and results. Section 5 concludes the study by exploring its implications, limitations, and future research directions.

2. Preliminaries

2.1 Neutrosophic Sets

A neutrosophic set $\acute{A}$ in a universal set $\acute{U}$ is defined by three membership functions: the truth-membership function $\acute{T}_{\acute{A}}(x)$, the indeterminacy-membership function $\acute{I}_{\acute{A}}(x)$ and the falsity-membership function $\acute{F}_{\acute{A}}(x)$. The neutrosophic set $\acute{A}$ is represented as:

$\acute{A} = (x, \left(\acute{T}_{\acute{A}}(x), \acute{I}_{\acute{A}}(x), \acute{F}_{\acute{A}}(x) \right) : x \in X$. where $\acute{T}_{\acute{A}}(x), \acute{I}_{\acute{A}}(x), \acute{F}_{\acute{A}}(x)$ is truth, Indeterminacy and falsity membership degree

where:

- $\acute{T}_{\acute{A}}(x)$ represents the degree of truth,
- $\acute{I}_{\acute{A}}(x)$ represents the degree of indeterminacy,
- $\acute{F}_{\acute{A}}(x)$represents the degree of falsity.

2.2 Neutrosophic Numbers

A neutrosophic number $\acute{N}$ is a triplet representing degrees of truth, indeterminacy, and falsity in uncertain data. It is defined as:

$$\acute{N} = \acute{T}_{\acute{N}}(x), \acute{I}_{\acute{N}}(x), \acute{F}_{\acute{N}}(x)$$

where:

- $\acute{T}_{\acute{N}}(x)$ is the truth-membership value $(0 \le \acute{T}_{\acute{N}}(x) \le 1)$
- $\acute{I}_{\acute{N}}(x)$ is the indeterminacy-membership value $(0 \le \acute{I}_{\acute{N}}(x) \le 1)$
- $\acute{F}_{\acute{N}}(x)$ is the falsity-membership value $(0 \le \acute{F}_{\acute{N}}(x) \le 1)$

The neutrosophic number provides a flexible way to model uncertain distances by accounting for various degrees of certainty.

2.3 Euclidean Distance in Three Dimensions

The Euclidean distance between two points $A=(a_1,b_1,c_1)$, $B=(a_2,b_2,c_2)$ and in three-dimensional space is given by: AB=$\sqrt{(a_2-a_1)^2+(b_2-b_1)^2+(c_2-c_1)^2}$

This distance formula captures the straight-line distance between two points in a 3D space, which is essential for accurately representing spatial relationships in problems where the third dimension plays a significant role, such as in certain logistics and routing tasks.

2. 4. Neutrosophic Euclidean Distance for TSP

For the Travelling Salesman Problem (TSP) involving uncertain distances, the Euclidean distance *d (A,B)* between any two points A and B is extended to a neutrosophic distance $D_N(A,B)$ defined as a triplet:

$$D_N(A,B)=(d_T,d_I,d_F)$$

where:

- d_T represents the truth value distance.
- d_I represents the indeterminacy value distance,
- d_F represents the falsity value distance.

Each component of $D_N(A,B)$ is calculated based on the application context, and this neutrosophic distance allows for a more flexible representation of the TSP by incorporating uncertainty directly into the distance measurements.

3. The greedy DM-TSP1 method

The novel greedy Dhouib-Matrix-TSP1 (DM-TSP1) is used to generate the Hamiltonian cycle and/or the open route (see Figure 2). Basically, DM-TSP1 is composed of four steps and repeated with (n-1) iterations (where n is the number of nodes) to generate the Hamiltonian cycle. Unless, to design an open route, DM-TSP1 requires only the first three steps (see Figure 2): The first step is composed of four tasks to initiate the DM-TSP1 with the assignment of the first connection (between two cities); the second step is used to find the *z* city characterized by its shortest distance; and the third step is required to discard the column of the *z* city and to update the list of *List-cities* (for more clarification see[22, 23]).

DM-TSP1 is applied to solve uncertain Travelling Salesmen Problem in [21, 22]. In addition, it is hybridized with the Artificial Bee Colony metaheuristic in [23], with the

Dhouib-Matrix-3 metaheuristic in [24, 25, 26] and the multi-start Dhouib-Matrix-4 in [27, 28, 29, 30, 31].

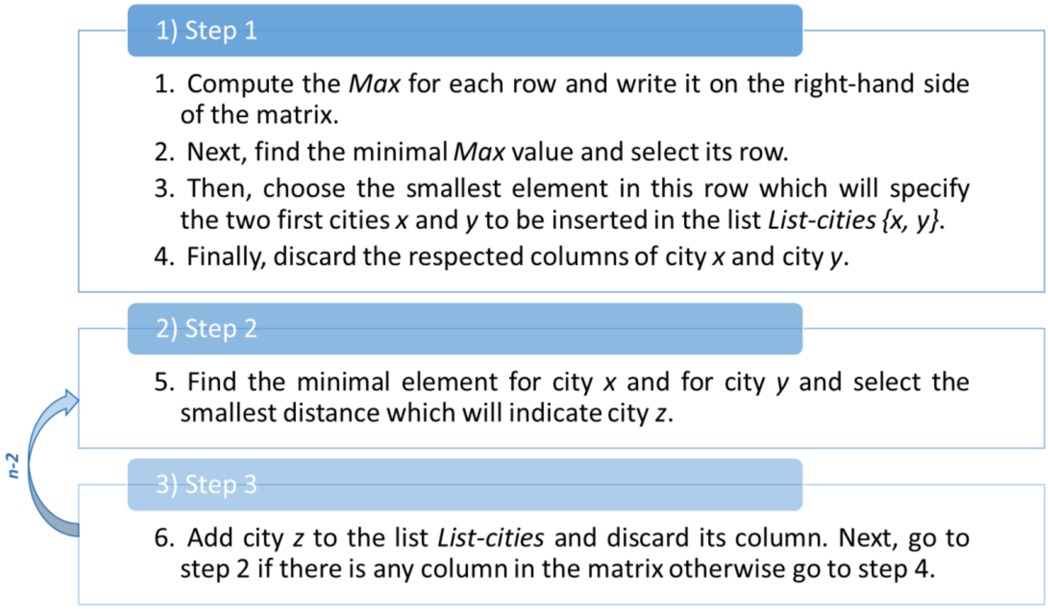

Figure 2. The general structure of the DM-TSP1 heuristic

DM-TSP1 is a component of the general concept of Dhouib-Matrix where other methods are designed such as the Dhouib matrix-TP1 in [32, 33], the Dhouib-Matrix-AP1 in [34, 35, 36, 37], the Dhouib-Matrix-MSTP in [38, 39] and the Dhouib-Matrix-SPP in [40, 41, 42, 43, 44, 45].

4. Numerical examples

In this section

Let us consider the example of seven nodes (n=7) with neutrosophic number introduced in [46]. The fitness function Eq. (1) is computed based on the distance, the highest-membership value and the minimal indeterminacy-membership value of the nodes neutrosophic numbers.

$$Fitness = \left(T_{\max} * D_N\right) \Big/ \left(I_{\min} + 1\right) \tag{1}$$

Where:

$T_{\max}$ is the highest truth-membership value of the node neutrosophic number (for the example presented in Table 2, the highest truth-membership number is 0.7, thus, $T_{\max} = 0.7$)

$I_{\min}$ is the minimal indeterminacy-membership value of the node neutrosophic number (for the example presented in Table 2, the minimal indeterminacy-membership number is 0.2, thus, $I_{\min} = 0.2$)

D_N is the neutrosophic distance of the generated route (for the solution generated by DM-TSP1 the D)

In addition, the distance between any two cities is computed not by using its coordinates (x and y) but by using their corresponding neutrosophic numbers (see Eq. (2)):

$$D_N(i,j)=\sqrt{(T_i-T_j)^2+(I_i-I_j)^2+(F_i-F_j)^2} \quad (2)$$

Moreover, a fitness improvement function Eq. 3 is used to compute the performance of DM-TSP1 versus GA algorithm

$$\text{Fitness improvement}=\left(\left(Fitness_{GA}-Fitness_{DM-TSP1}\right)/Fitness_{DM-TSP1}\right)*100 \quad (3)$$

Where:

$Fitness_{GA}$ is the fitness result created by the GA algorithm

$Fitness_{DM-TSP1}$ is the fitness result generated by DM-TSP1

Table 1 summarize the geographical positions of the seven cities (these coordinates are used only for the graphical representation).

Table 1. the geographical positions of the seven cities

City	*X* coordinate	*Y* coordinate
1	0	0
2	1	1
3	2	0
4	1	2
5	3	1
6	2	3
7	4	2

Figure 3 depicts the graphical representation of the case study of seven cities.

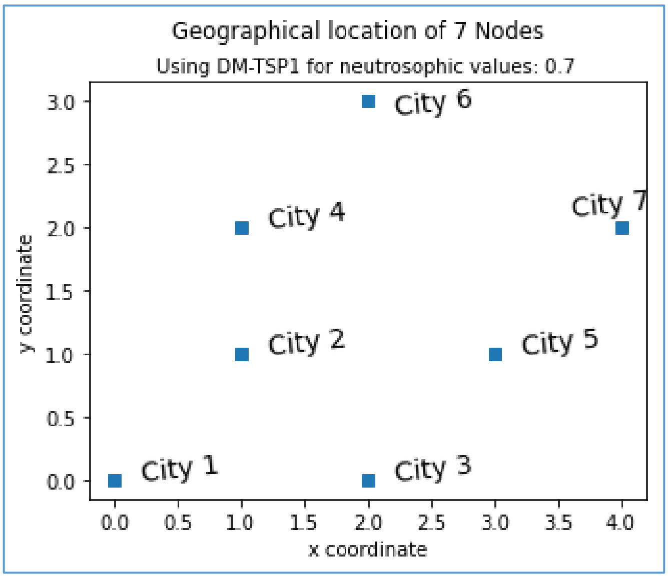

Figure 3. The graphical representation of the seven cities

Actually, for each city a simple neutrosophic number (the value for each function is between 0 and 1) is specified in Table 2.

Table 2. The neutrosophic number of each city

City	Neutrosophic value
1	(0.7, 0.2, 0.1)
2	(0.6, 0.3, 0.1)
3	(0.5, 0.3, 0.2)
4	(0.2, 0.5, 0.3)
5	(0.4, 0.4, 0.2)
6	(0.3, 0.4, 0.3)
7	(0.6, 0.3, 0.1)

Before starting the DM-TSP1 method the contingency matrix (see Figure 4) is generated by computing the Euclidian distance (using the neutrosophic numbers) between all cities using Eq. (2). For example, to compute the distance between cities 1 and 2 the distance is computed by $D_N(1,2)=\sqrt{(0.7-0.6)^2+(0.2-0.3)^2+(0.1-0.1)^2}=0.14$.

$$\begin{pmatrix} 0.00 & 0.14 & 0.24 & 0.62 & 0.37 & 0.49 & 0.14 \\ 0.14 & 0.00 & 0.14 & 0.49 & 0.24 & 0.37 & 0.00 \\ 0.24 & 0.14 & 0.00 & 0.37 & 0.14 & 0.24 & 0.14 \\ 0.62 & 0.49 & 0.37 & 0.00 & 0.24 & 0.14 & 0.49 \\ 0.37 & 0.24 & 0.14 & 0.24 & 0.00 & 0.14 & 0.24 \\ 0.49 & 0.37 & 0.24 & 0.14 & 0.14 & 0.00 & 0.37 \\ 0.14 & 0.00 & 0.14 & 0.49 & 0.24 & 0.37 & 0.00 \end{pmatrix}$$

Figure 4. The contingency matrix

The next step consists on calculating the maximum of each row and insert it on the right-hand side of the matrix. Besides the minimal value (0.37) is selected (see Figure 5).

∞	0.14	0.24	0.62	0.37	0.49	0.14	0.62
0.14	∞	0.14	0.49	0.24	0.37	0.00	0.49
0.24	0.14	∞	0.37	0.14	0.24	0.14	0.37
0.62	0.49	0.37	∞	0.24	0.14	0.49	0.62
0.37	0.24	0.14	0.24	∞	0.14	0.24	0.37
0.49	0.37	0.24	0.14	0.14	∞	0.37	0.49
0.14	0.00	0.14	0.49	0.24	0.37	∞	0.49

Figure 5. The maximum value for each row is inserted at right

Besides, the DM-TSP1 requires only six (n-1) iterations to create a solution. Figure 6 illustrates a step-by-step application of DM-TSP1. At first, DM-SPP selects the element at the position (d_{21}) and discard column 1 and 2 (see Figure 6.1). At second, DM-SPP selects the element at the position (d_{16}) and discard column 6 (see Figure 6.2). At third, the element at the position (d_{60}) is selected and the column 0 is discarded (see Figure 6.3). Besides, the element at the position (d_{24}) is selected and the column 4 is discarded (see Figure 6.4). Next, the element at the position (d_{45}) is selected and the column 5 is discarded (see Figure 6.5). Finally, the element at the position (d_{53}) is selected and the column 3 is discarded (see Figure 6.6).

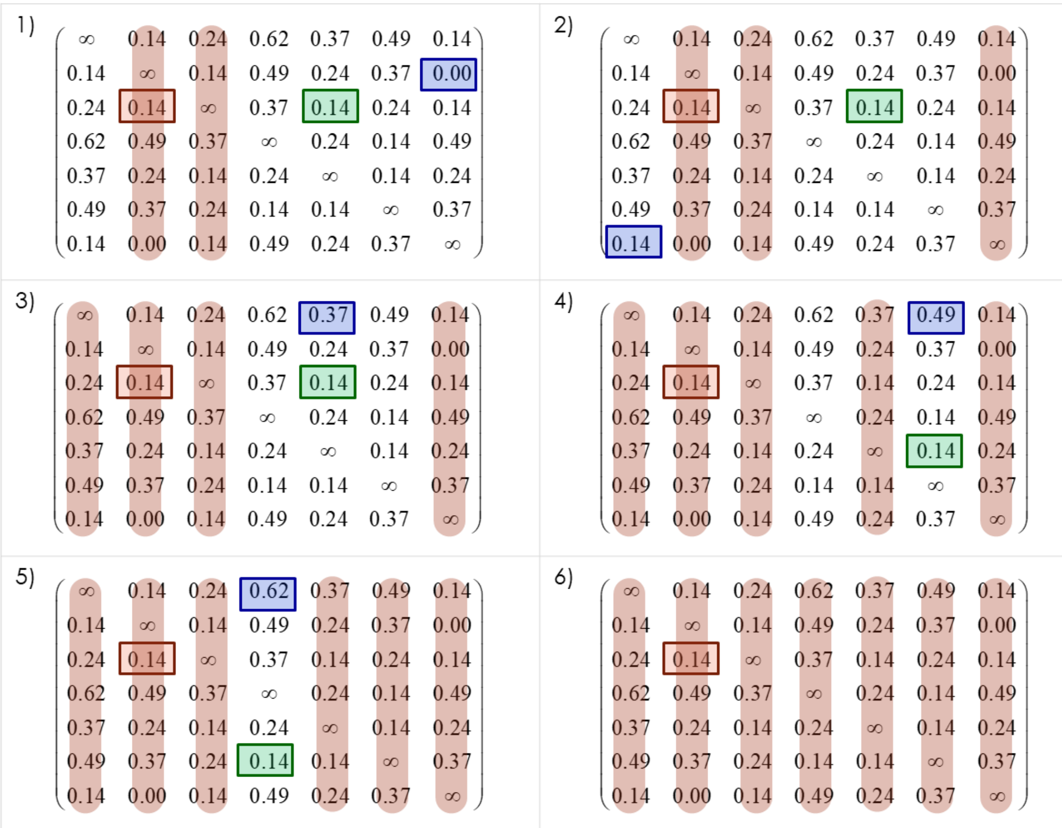

Figure 6. The step-by-step application of DM-TSSP1 on seven nodes problem

Therefore, the generated route by DM-TSP1 is [1-7-2-3-5-6-4] with a value of 0.7 (see Figure 7).

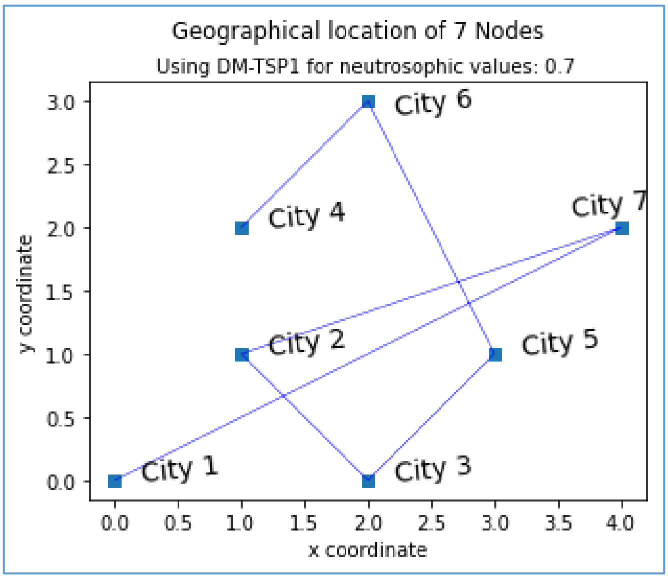

Figure 7. The shortest route generated by DM-TSP1

By using the Fitness function Eq. (1) based on the maximum truth- membership (0.7) and minimum indeterminacy- membership (0.2) the generated solution by DM-TP1 will be (0.41). Whereas, the value generated by the GA developed by [46] is (0.79). Indeed, the proposed DM-TSP1 heuristic presents a Fitness improvement of (92.68% = ((0.79-0.41)/0.41)*100) to the Genetic Algorithm developed in [46]. Moreover, DM-TSP1 generates this solution after just simple six iterations.

Table 3. The solutions generated by DM-TSP1 and GA

Methods	**Shortest distance**	**Fitness**	**Fitness improvement**
GA	1.35	0.79	92.68%
DM-TSP1	0.70	0.41	00.00%

5. Conclusions

This paper presented a three-dimensional Euclidean distance model combined with neutrosophic numbers to address uncertainty in the Travelling Salesman Problem (TSP) by using the novel Dhouib-Matrix-TSP1 (DM-TSP1) heuristic. This approach, DM-TSP1, enhances the traditional TSP models by accommodating both spatial complexity and indeterminate distance values, offering a realistic framework for practical applications where uncertainty is prevalent. The proposed model demonstrates improved adaptability and robustness in environments with ambiguous data, making it valuable for fields like logistics and complex routing. Future research can expand on this work by exploring computational efficiency and scalability, further enhancing its application in optimization under uncertain conditions.

Conflicts of Interest: The authors declare no conflict of interest.

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