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Solving the shortest path based on the traveling salesman problem with a genetic algorithm in a Fermatean neutrosophic environment

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Abstract: The Traveling Salesman Problem (TSP) is one of the most significant and well-known optimization problem that is frequently limited by uncertainty in edge lengths. Existing methods fail to effectively model and solve such problems in uncertain environments. To address this gap, we propose a novel approach that combines a genetic algorithm (GA) with Fermatean neutrosophic numbers to provide a more robust representation of uncertainty. This work presents a comprehensive framework for evaluating the shortest path in a given network by precisely characterizing uncertain edge lengths. The proposed methodology is tested on various TSP scenarios of varying complexities, demonstrating its ability to generate near-optimal solutions with higher efficiency and accuracy than traditional techniques. Our findings highlight the method's potential for advancing uncertain route optimization and have significant practical implications for real-world logistics.

Keywords: Fermatean neutrosophic number; Genetic algorithm; Traveling salesman problem; Shortest path problem

1. Introduction

Evaluating the shortest path in real-world networks represents a critical optimization challenge, particularly under uncertain conditions where traditional real numbers fail to capture ambiguity effectively. To address this limitation, researchers have adopted fuzzy numbers as edge weights. Prof. Zadeh [1] introduced fuzzy sets to manage uncertainty using membership functions. Building on this, Atanassov [2] developed intuitionistic fuzzy sets (IFS) to incorporate both membership and non-membership degrees, enhancing the capacity to handle ambiguity. After that, Smarandache [3] suggested neutrosophic sets (NS), which include three memberships. Expanding on these concepts, Raut, P. K. [4] introduced Fermatean neutrosophic sets (FNS) by integrating Fermatean fuzzy sets with neutrosophic sets, gaining significant attention in research. Recent studies by Raut, P. K. et al. [5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15] and Chakraborty, A. [16, 17] have extended these concepts, particularly in neutrosophic and Fermatean neutrosophic environments.

The TSP is a renowned NP-hard optimization challenge in mathematics and computer science, was initially formulated in the 1930s, gaining prominence post-1950 [18, 19, 20]. The problem involves a salesman traveling through a different city, returning to the initial vertex while minimizing travel cost or distance. Addressing TSP under uncertain conditions, such as variable transportation costs and times influenced by weather or traffic, presents a complex challenge for decision-makers. Fuzzy sets offer a solution by enabling decision-making with imprecise data. Numerous studies [21, 22, 23] have explored on related to fuzzy TSP.

To address these challenges, many researchers have introduced exact, heuristic, and metaheuristic algorithms for TSP. Exact methods offer optimal solutions but become computationally infeasible for larger networks. Heuristic and metaheuristic approaches, such as genetic algorithms, ABC algorithms, and harmony search methods, are more efficient in reducing computational time. Genetic algorithms, which simulate evolutionary processes, stand out for their adaptability. They employ genetic operations like selection, crossover, and mutation to evolve solutions iteratively, demonstrating their efficacy in evaluating TSP and other optimization problems [24, 25, 26, 27, 28, 29, 30].

This study focuses on solving TSP using a genetic algorithm that incorporates Fermatean neutrosophic numbers to represent arc lengths, addressing the limitations of standard evolutionary methods under uncertainty. The proposed approach integrates a novel mathematical model for Fermatean neutrosophic arc lengths and introduces innovative crossover and mutation in the genetic algorithm. To validate the methodology, a numerical example illustrates.

This research article is organized in following sections: In Section-2 explains motivation, In Section-3 research gaps, and in Section-4 presents a flow chart. Section-5 reviews foundational concepts of neutrosophic and Fermatean neutrosophic theories. Section-6 explains the genetic algorithm framework. Section-7 presents the mathematical model for the Fermatean neutrosophic TSP. Section-8 details the proposed evolutionary method. Section-9 evaluates the experimental results, and Section-10 presents the conclusion.

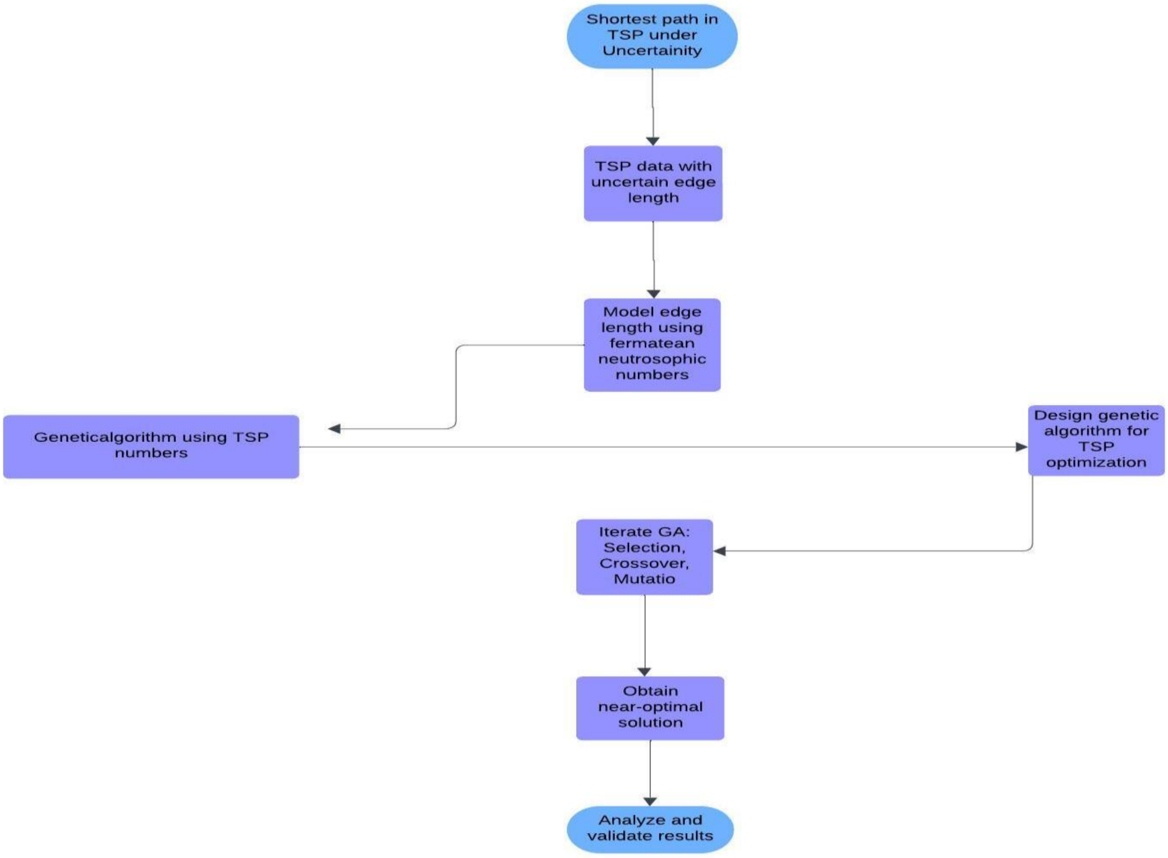
2. Motivation

We emphasized the critical challenges associated with solving the Traveling Salesman Problem (TSP) in uncertain environments, where traditional methods fail to adequately handle the complexities introduced by imprecise and uncertain data. We also discussed the increasing demand for effective and realistic optimization techniques in fields like logistics, transportation, and network design, which are frequently affected by uncertainty in edge lengths.

3. Research Gap

We identified the lack of robust methodologies for addressing the TSP under uncertain conditions as a significant gap in the current literature. While existing approaches use fuzzy or neutrosophic numbers, their ability to express higher degrees of uncertainty and interdependencies is limited. This gap motivated our exploration of Fermatean neutrosophic numbers, which provide a more precise and flexible framework for modelling uncertainty. Our work introduces a novel integration of genetic algorithms with Fermatean neutrosophic numbers to evaluate the shortest path in a network. This approach not only enhances the representation of uncertainty but also improves the efficiency and accuracy of obtaining near-optimal solutions compared to conventional techniques.

4. Flowchart representing the proposed approach



5. Preliminaries

5.1 Neutrosophic set [5]

Neutrosophic set is an extension of Intuitionistic fuzzy sets, allowing for the representation of uncertainty, vagueness, and indeterminacy.

A Neutrosophic set A is defined as $A = (\breve{x}, \left(\breve{T}_{\breve{A}}(\breve{x}), \breve{I}_{\breve{A}}(\breve{x}), \breve{F}_{\breve{A}}(\breve{x})\right) : \breve{x} \in \breve{X}$.

$\breve{x} \in U$, $0 \leq \breve{T}_{\breve{A}}(\breve{x}) + \breve{I}_{\breve{A}}(\breve{x}) + \breve{F}_{\breve{A}}(\breve{x}) \leq 3$

$\breve{T}_{\breve{A}}(\breve{x})$, $\breve{I}_{\breve{A}}(\breve{x})$, $\breve{F}_{\breve{A}}(\breve{x})$represents degree of truth, indeterminacy and falsity membership respectively.

5.2 Fermatean neutrosophic set [13]

A Fermatean neutrosophic set A in a given universe of discourse U is characterized by three membership functions:$\breve{T}_{\breve{A}}(\breve{x}), \breve{I}_{\breve{A}}(\breve{x}), \breve{F}_{\breve{A}}(\breve{x})$. These functions assign to each element $\breve{x} \in U$ a value within the interval [0,1].

Fermatean neutrosophic set A is defined as:$A = (\breve{x}, \left(\breve{T}_{\breve{A}}(\breve{x}), \breve{I}_{\breve{A}}(\breve{x}), \breve{F}_{\breve{A}}(\breve{x})\right) : \breve{x} \in \breve{X}$.

$0 \leq (\breve{T}_{\breve{A}}(\breve{x}))^3 + (\breve{F}_{\breve{A}}(\breve{x}))^3 \leq 1$, $0 \leq (\breve{I}_{\breve{A}}(\breve{x}))^3 \leq 1$.

and sum cube of this three-membership degree lies in between [0, 2] i.e. $0 \leq (\breve{T}_{\breve{A}}(\breve{x}))^3 + (\breve{I}_{\breve{A}}(\breve{x}))^3 + (\breve{F}_{\breve{A}}(\breve{x}))^3 \leq 2$.

5.3 Euclidean Distance between Fermatean Neutrosophic numbers

The Euclidean Distance is a common metric used to measure the distance between two vertices or entities in space. When applied to Fermatean Neutrosophic Numbers (FNNs), which are an extension of neutrosophic numbers, the Euclidean Distance is computed by taking into account the three memberships.

For two Fermatean Neutrosophic Numbers, $\boldsymbol{A} = (\breve{\boldsymbol{T}}_1, \breve{\boldsymbol{I}}_1, \breve{\boldsymbol{F}}_1)$, $\boldsymbol{B} = (\breve{\boldsymbol{T}}_2, \breve{\boldsymbol{I}}_2, \breve{\boldsymbol{F}}_2)$ the Euclidean Distance is defined as

$$d(A,B) = \sqrt{(\breve{T}_1 - \breve{T}_2)^2 + (\breve{I}_1 - \breve{I}_2)^2 + (\breve{F}_1 - \breve{F}_2)^2}$$

6. Genetic algorithm

The TSP is a most significant optimization problem in the domains of computational science and mathematics. The problem relates to a salesman that begins on a journey to multiple cities before returning to the initial location. This problem has been extensively studied due to its high complexity and practical applications in logistics, network routing, and mapping. While exact algorithms can solve TSP for small problem sizes, they become computationally infeasible as the number of cities increases.

The ideas behind natural genetics are known as genetic algorithms.

This is a powerful metaheuristic approach for solving TSP, offering approximate solutions that can be close to the optimal solution in reasonable computation times. This proposed GA for evaluating the shortest path aims to optimize the TSP by leveraging the principles of evolution.

Objective: The aim of this suggested genetic algorithm (GA) is to identify the most efficient path that starts from a particular city, visits other cities, and then backs to the initial city while minimizing the overall distance traveled.

7. Proposed Methodology

Encoding: Each individual in the population will be encoded as a sequence of integers representing the order of cities to visit, where each integer corresponds to a unique city.

Initialization: A population of potential solutions will be randomly generated, each representing a different permutation of cities. The population size should be large enough to explore a diverse set of solutions.

Fitness Evaluation: The assessment of each individual's fitness in the population is evaluated by the total distance covered following the sequence of cities in their permutation.

Selection: Individuals with greater fitness scores are more likely to be chosen as parents for reproduction.

Crossover: The selected parents will undergo crossover, where their genetic material (permutation of cities) is combined to create offspring.

Mutation: To introduce diversity into the population, a mutation operator is applied to randomly alter the genetic material of some individuals. Mutation can involve swapping or inserting a city in a particular position.

Survival Selection and Termination: The next generation is formed by choosing a specific number of individuals from both the offspring and the existing population, prioritizing higher fitness levels. The cycle of selection, crossover, and mutation continues until a termination criterion is fulfilled.

Result: Once the termination condition is satisfied, the optimal individual in the final population will indicate the shortest path discovered for the TSP.

8. The pseudocode of the genetic algorithm for Fermatean neutrosophic shortest path

Generate an initial population of chromosomes.
Assess the fitness of each chromosome within the population.
Continue executing the given directions until the final condition is satisfied:

Selection:

Choose individuals as parents from the population according to their level of fitness.
Utilize selection methods to select individuals.

Crossover:

Create offspring by merging genetic material from chosen parents. Apply several crossover approaches, such as one-point crossover phenomenon, two-point crossover phenomenon, uniform crossover phenomenon, and others.

Mutation:

Apply mutation to the offspring to introduce genetic diversity
Perform mutation techniques such as bit-flip mutation, swap mutation, inversion mutation, etc.
Evaluate fitness of new individuals

Replacement:

Choose specific individuals to propagate to the subsequent generation, replacing the previous population.
Perform replacement strategies such as generational replacement, elitism, etc.

Termination condition:

Verify whether the termination condition has been satisfied, if satisfied then end.
Return the best most optimal individual found in the final population as the solution

9. Development of a Fermatean Neutrosophic Model for the TSP

The formulation of a Fermatean neutrosophic TSP involves introducing Fermatean neutrosophic or uncertain parameters into the traditional TSP formulation. The goal is to optimize the tour or route of a salesman that begins on a journey to multiple cities before returning to the stating city, while considering the uncertainty or imprecision associated with certain parameters such as distances, costs, times, or demands.

The Fermatean neutrosophic TSP can be defined as follows:

Consider x_{ij} defined a binary decision variable, where $\begin{cases} x_{ij} = 1, \text{if the salesman visits} \\ x_{ij} = 0, \quad \text{otherwise.} \end{cases}$

Reducing the overall cost, distance, or time of the routes, which can be defined as: minimize $Z = \sum\sum c_{ij} * x_{ij}$

Constraints:

a. Ensure that each city is visited exactly once: $\sum x_{ij} = 1, \forall j \in \text{Cities}$

b. Ensure that the salesman back to the initial city: $\sum x_{ij} = 1$

c. Eliminate subtours (subsets of cities that do not include the starting city): $\sum x_{ij} \leq n-1$, for all $i \in \text{Cities}, i \neq 1 \sum xij - \sum xji \leq 0$.

Fermatean neutrosophic Parameters: The uncertain parameters, such as distances or costs, can be represented as Fermatean neutrosophic numbers. This involves assigning degrees of membership to different values or intervals of the parameters.

Fermatean neutrosophic Objective Function: The objective function can incorporate Fermatean neutrosophic sets to represent the uncertainty. This can involve maximizing or minimizing a Fermatean neutrosophic value, Fermatean neutrosophic interval, or Fermatean neutrosophic set representing the costs, distances, or time considering their fuzziness.

Fermatean neutrosophic Constraints: The constraints can also employ Fermatean neutrosophic sets to represent the uncertainty associated with parameters. These constraints can include Fermatean neutrosophic equalities or inequalities, where membership degrees are used to model the degree of satisfaction or violation of a constraint.

10. Numerical example

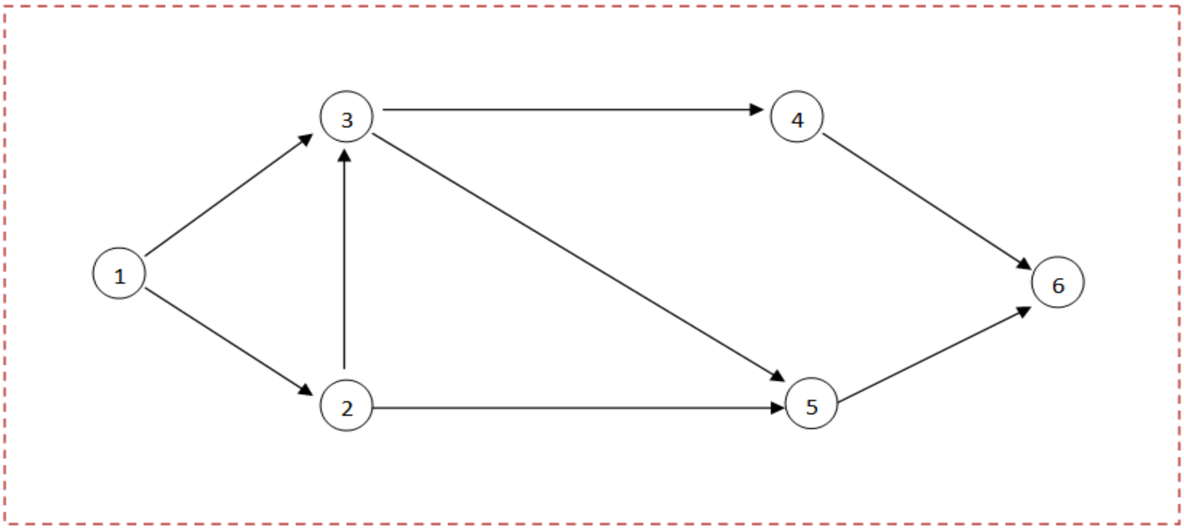


Fig. 1: Routes of TSP with Fermatean neutrosophic number

Step-1: Initialization:

In Table-1, we consider an initial population. We construct a 6-node network consisting of five routes, each of which is arrangement of the 6 cities given in Table 2. The Fermatean neutrosophic number ($\breve{T}$, $\breve{I}$, $\breve{F}$) represents each city.

Table-1. 6 cities edge lengths

City	Fermatean Neutrosophic number
1	<0.6,0.3,0.1>
2	<0.5, 0.3, 0.2>
3	<0.3, 0.6, 0.1>
4	<0.1, 0.7, 0.3>
5	<0.2, 0.1, 0.7>
6	<0.4, 0.4, 0.2>

Table-2. Possible routes

Route no	Possible route
1	$1 \to 2 \to 3 \to 4 \to 6$
2	$1 \to 3 \to 4 \to 6$
3	$1 \to 3 \to 5 \to 6$
4	$1 \to 2 \to 5 \to 6$
5	$1 \to 2 \to 3 \to 5 \to 6$

Step 2: Evaluation (Fitness):

We evaluate the fitness of every route by employing a specific fitness function. In this instance, the function incorporates Fermatean neutrosophic numbers and is designed to minimize the overall distance, taking into consideration any inherent uncertainty.

$$\text{Fitness} = \sum \frac{(T_i * (d_i))}{(I_i + 1)}$$

Where:

T_i denote the node's highest values

I_i denote the node's lowest values

(d_i) denote the is the interval separating two adjacent nodes along the route.

Table-3: Finding Fitness value for first Route by using definition-2.3

Distance between node	Crisp value
1-2	0.14
1-3	0.42
2-3	0.37
2-5	0.61
3-4	0.30
3-5	0.78
4-6	0.42
5-6	0.61

Final Distance =0.14+0.37+0.30+0.42=1.23

$$\text{Fitness} = \sum \frac{(0.6 * 1.23)}{(0.1 + 1)}$$

$$\text{Fitness} = \sum \frac{(0.738)}{(1.1)} = 1.99$$

Similarly, we evaluate 5 Routes

Table-4: Route fitness

Fitness function of Route	Minimize distance
1	1.99
2	0.62
3	0.98
4	0.74
5	1.03

Step 3: Route Selection (Choosing Two Routes):

Utilize a selection method to evaluates the routes that will serve as parents for the next generation. This process increases the likelihood of selecting routes with lower fitness values.

Chosen Routes:

The two routes lowest fitness values are as follows:

- Fitness value of Route 2 is 0.62
- Fitness value of Route 4 is 0.74

Step-4 Crossover (Recombination):

Perform a crossover operation on the selected routes to generate new offspring routes, ensuring the procedure aligns with the framework of neutrosophic numbers.

Genetic Information Combination:

- Parent Route 4: [1, 2, 5, 6]
- Parent Route 2: [1, 3, 4, 6]

Crossover Point after Node 1

- Initial Offspring Route: [1 | 3, 4, 6]

Finalizing the Offspring:

To finalize the offspring, add the missing nodes from the other parent without creating duplicates:

- Final Offspring Route: [1, 3, 4, 6]

Step 5: Mutation (Swapping Two Random Nodes):

Introduce minor random changes to the routes through mutation operators while ensuring compliance with neutrosophic number constraints. For example, swapping nodes 4 and 3 results in the following:

- Mutated Offspring Route: [1, 3, 4, 6]

Step 6: Replacement (Substituting a Parent):

Replace certain existing routes in the population with newly mutated offspring to produce the next generation. For instance, one of the parent routes (e.g., Route 3) can be substituted with the mutated offspring:

- Updated Population: [1, 3, 4, 6]

Step 7: Termination:

This procedure is iteratively performed over multiple generations, progressively improving the solutions. The process ends once the established stopping condition is met. This given example illustrates how a Genetic Algorithm (GA) is used for solving the Traveling Salesman Problem (TSP) in a 6-node network with Fermatean neutrosophic numbers. Advanced genetic operators and fitness evaluation techniques are typically applied in practice to enhance optimization performance.

10. Result: The optimal path determined using Traveling Salesman Problem with Fermatean neutrosophic numbers.

Table 5. The best result of SP

The shortest path problem for FTSP was addressed using linear programming techniques in LINGO software.	Proposed Genetic Algorithm for FTSP Shortest Path:
Minz=0.62	Cost =0.62 and shortest route= $1 \rightarrow 3 \rightarrow 4 \rightarrow 6$

In the given numerical example, the traveling salesman problem of neutrosophic graphs is solved by applying our proposed GAs. We consider six nodes in Figure-1 and the five pathways in Table-2. In this Traveling Salesman problem, we used a genetic algorithm approach to evaluate the SP of given network, and this is the novel idea we applied for fermatean neutrosophic numbers. The first example shows how our suggested method and language program may discover the best possible shortest path. According to Table-5, the shortest path and cost were same in both instances.

11. A comparative analysis of our approach with alternative methodologies.

Table 4. Comparison of the shortest path and its associated cost.

Methodology	Shortest path	Shortest path cost
Begum, S. G. et al. [30]	3→1→2→4→5→ 6→7	1.86
Dey, A. et al. [31]	3 →1→ 2→ 4→ 5→ 6→7	1.02
Raut, P. K. et al. [32]	3 →1→2→4→5→ 6→7	0.86
Our proposed method in Fermatean Neutrosophic environment	1 → 3 → 4 → 6	0.62

Study	Methodology	Environment	Shortest Path Length	Strengths	Limitations
Begum, S. G. et al. [30]	Applied an intuitionistic fuzzy set for shortest path evaluation	fuzzy environment	Moderate	Improved handling of hesitation and vagueness in uncertain conditions	Limited scalability for complex real-world networks
Dey, A. et al. [31]	Used a fuzzy-based approach to solve the shortest path problem	Fuzzy environment	Slightly better than [30]	Handles moderate uncertainty well and provides computational efficiency	Lacks precision in modelling higher-order uncertainty
Raut, P. K. et al. [32]	Leveraged a genetic algorithm with neutrosophic numbers	Neutrosophic environment	Better than [31]	Superior uncertainty modeling compared to fuzzy methods and more robust optimization	Computational cost is higher due to the complexity of neutrosophic operations

Our Proposed Method	Combines a genetic algorithm with Fermatean neutrosophic numbers	Fermatean neutrosophic environment	Best result	Achieves the most precise uncertainty modeling and delivers highly efficient solutions	Requires extensive testing in dynamic and real-world applications

We compared our proposed method with three existing methods [30, 31, 32], and the results demonstrate that the new approach is more effective for evaluating the shortest path in a Fermatean neutrosophic environment**.**

12. Conclusions

In this research, we addressed the classic Traveling Salesman Problem (TSP) by integrating a genetic algorithm (GA) with a Fermatean neutrosophic environment, providing a robust framework for solving optimization problems under uncertainty. The proposed approach leverages the exploratory power of GAs to efficiently navigate large search spaces and the flexibility of Fermatean neutrosophic numbers to accurately model uncertainty and imprecision in edge lengths. Through a detailed numerical example, we demonstrated the effectiveness of our method in generating near-optimal solutions. The results highlight the practical applicability of the proposed approach in various domains, such as logistics, transportation networks, and other optimization scenarios that can be modelled as TSP.in future we Explore the integration of genetic algorithms with other metaheuristic methods, such as particle swarm optimization or ant colony optimization, to further enhance solution quality and convergence speed.

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