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A Hybrid Fuzzy MCDM Framework for Smart City Infrastructure Prioritization

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Abstract:

The rapid growth of urbanization and technological advancements has led to the emergence of smart cities, where efficient infrastructure planning plays a crucial role in ensuring sustainable development and improved quality of life. Prioritizing smart city infrastructure projects involves evaluating multiple conflicting criteria such as economic feasibility, environmental sustainability, technological readiness, social impact, and resource constraints. These criteria are often characterized by uncertainty and vagueness due to subjective human judgments and incomplete information.

In this paper, a hybrid fuzzy multi-criteria decision-making (MCDM) framework is proposed for smart city infrastructure prioritization under uncertainty. The proposed model integrates fuzzy Analytic Hierarchy Process (AHP), fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and goal programming to provide a comprehensive decision-support system. Fuzzy AHP is employed to determine the relative importance of evaluation criteria using linguistic assessments, while fuzzy TOPSIS is utilized to rank infrastructure alternatives based on their closeness to ideal solutions. Furthermore, goal programming is incorporated to optimize the satisfaction of multiple decision objectives and ensure balanced resource allocation.

A numerical case study is presented to demonstrate the applicability and effectiveness of the proposed framework. The results indicate that the hybrid fuzzy MCDM approach provides consistent, robust, and reliable prioritization outcomes, enabling decision makers to effectively manage complex urban infrastructure planning problems. The proposed model can serve as a valuable tool for policymakers, urban planners, and engineers in the development of sustainable and intelligent smart city systems.

Keywords: Fuzzy sets, Multi-criteria decision making, Fuzzy AHP, Fuzzy TOPSIS, Goal programming.

1. Introduction

The rapid pace of urbanization across the globe has significantly transformed the way cities function, leading to increased demand for efficient infrastructure, sustainable resource management, and improved quality of life. According to recent global estimates, more than half of the world's population resides in urban areas, and this proportion is expected to rise steadily in the coming decades. As a result, cities face critical challenges such as traffic congestion, energy shortages, environmental degradation, and inadequate public services. In response to these challenges, the concept of smart cities has emerged as a comprehensive approach to urban development that integrates advanced technologies, data-driven decision-making, and sustainable planning strategies.

A smart city can be broadly defined as an urban system that leverages information and communication technologies (ICT), Internet of Things (IoT), and intelligent infrastructure to enhance the efficiency of urban services and improve citizens' well-being. Smart city initiatives encompass a wide range of domains, including transportation, energy management, water supply, waste management, healthcare, and governance. However, one of the most critical aspects of smart city development is the prioritization of infrastructure projects. Given limited financial, technical, and human resources, decision makers must identify which infrastructure investments should be implemented first to maximize overall societal benefit.

Infrastructure prioritization in smart cities is inherently a complex decision-making problem involving multiple and often conflicting criteria. These criteria may include economic factors such as cost and return on investment, environmental factors such as sustainability and carbon emissions, social factors such as public acceptance and equity, and technical factors such as feasibility and reliability. Furthermore, the decision-making process is often complicated by uncertainty and ambiguity, as many criteria are evaluated based on subjective judgments and incomplete information.

Multi-criteria decision-making (MCDM) techniques have been widely used to address such complex decision problems. MCDM methods provide systematic frameworks for evaluating alternatives based on multiple criteria and have been applied in various domains including engineering design, supply chain management, environmental planning, and urban development. Among the most widely used MCDM methods is the Analytic Hierarchy Process (AHP), introduced by Saaty [18], which decomposes a complex decision problem into a hierarchical structure and determines the relative importance of criteria through pairwise comparisons.

Another prominent method is the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), developed by Hwang and Yoon [5], which ranks alternatives based on their distance from ideal and negative-ideal solutions.

Despite their effectiveness, classical MCDM methods typically assume that decision data are precise and deterministic. In real-world smart city applications, however, decision makers often rely on linguistic assessments such as "high", "medium", or "low" to express their preferences. These qualitative assessments involve inherent vagueness and uncertainty that cannot be adequately represented using crisp numerical values. To address this limitation, fuzzy set theory, introduced by Zadeh [29], has been extensively used to model uncertainty and imprecision in decision-making processes.

Fuzzy set theory allows elements to have partial membership in a set, thereby providing a flexible mathematical framework for representing uncertain information. Bellman and Zadeh [1] extended fuzzy set theory to decision-making environments, demonstrating how fuzzy logic can be used to model complex decision processes involving multiple objectives and constraints. Subsequent developments by Zimmermann [30] and Klir and Yuan [9] further strengthened the theoretical foundation of fuzzy decision analysis.

The integration of fuzzy set theory with MCDM methods has led to the development of fuzzy MCDM approaches such as fuzzy AHP and fuzzy TOPSIS. In fuzzy AHP, pairwise comparisons are expressed using fuzzy numbers, allowing decision makers to incorporate uncertainty and subjective judgments more effectively. Buckley [2] proposed one of the earliest fuzzy extensions of the AHP method. Similarly, Chen [3] extended the TOPSIS method to handle fuzzy data, enabling group decision-making under uncertain environments.

Over the past decade, fuzzy MCDM methods have gained significant attention in smart city planning and infrastructure management. Researchers have applied fuzzy decision models to evaluate urban transportation systems, prioritize renewable energy projects, and assess sustainable infrastructure alternatives. For instance, Govindan [4] applied fuzzy MCDM techniques for sustainable supplier evaluation, while Liu [11] developed a fuzzy decision framework for energy system evaluation. Similarly, Rao [15] and Singh [20] demonstrated the effectiveness of hybrid fuzzy MCDM approaches in infrastructure and energy planning.

Recent studies have emphasized the importance of hybrid decision-making frameworks that combine multiple MCDM techniques to improve decision accuracy and robustness. Mardani et al. [12] provided a comprehensive review of MCDM methods and highlighted the growing trend toward hybrid models. Velasquez and Hester [24] also emphasized that no single MCDM method is sufficient to address all aspects of complex decision problems, and hybrid approaches are often necessary.

In the context of smart city infrastructure prioritization, hybrid fuzzy MCDM models offer several advantages. First, they enable the integration of multiple evaluation criteria, including economic, environmental, social, and technical factors. Second, they provide a systematic approach for handling uncertainty and linguistic information. Third, they allow decision makers to combine subjective judgments with quantitative analysis, leading to more balanced and informed decisions.

Another important aspect of modern decision-making is the incorporation of optimization techniques. Goal programming is a widely used optimization method that allows decision makers to handle multiple conflicting objectives simultaneously. Unlike traditional optimization methods that focus on a single objective, goal programming minimizes deviations from desired target levels across multiple goals. This makes it particularly suitable for smart city planning, where decision makers must balance competing objectives such as cost reduction, environmental sustainability, and social welfare.

The integration of goal programming with fuzzy MCDM methods provides a powerful framework for solving complex decision problems. Fuzzy goal programming allows decision makers to express aspiration levels using linguistic terms and handle uncertainty in both objectives and constraints. This approach enhances the flexibility and adaptability of decision models, making them more suitable for real-world applications.

In recent years, the application of hybrid fuzzy decision models in smart city planning has gained considerable attention. Patel [14] proposed a fuzzy MCDM framework for infrastructure prioritization in sustainable cities, while Liu [10] developed a multi-criteria decision model for smart city planning. Wang [26] further explored the integration of artificial intelligence with fuzzy decision-making techniques for urban planning applications. These studies highlight the growing importance of advanced decision-support systems in the development of smart and sustainable cities.

Despite these advancements, several challenges remain in the application of fuzzy MCDM models to smart city infrastructure prioritization. Many existing studies focus on single-method approaches or limited hybrid models, which may not fully capture the complexity of real-world decision environments. Furthermore, optimization aspects are often overlooked, limiting the ability of decision models to achieve balanced outcomes across multiple objectives.

To address these limitations, this paper proposes a hybrid fuzzy multi-criteria decision-making framework that integrates fuzzy AHP, fuzzy TOPSIS, and goal programming for smart city infrastructure prioritization. The proposed model combines hierarchical criteria weighting, distance-based alternative ranking, and optimization-based decision support within a unified framework. By integrating these complementary techniques, the model aims to improve the accuracy, robustness, and practicality of infrastructure prioritization decisions.

The main contributions of this study are summarized as follows:

(i) A hybrid fuzzy MCDM framework integrating fuzzy AHP, fuzzy TOPSIS, and goal programming is developed for smart city infrastructure prioritization.

(ii) The proposed model effectively incorporates uncertainty and linguistic information using fuzzy numbers.

(iii) The framework provides a systematic approach for evaluating and ranking infrastructure alternatives based on multiple criteria.

(iv) The integration of goal programming enhances decision-making by optimizing the satisfaction of multiple objectives.

(v) A numerical case study is presented to demonstrate the applicability and effectiveness of the proposed approach.

The remainder of this paper is organized as follows. Section 2 presents the mathematical preliminaries related to fuzzy sets and decision-making methods. Section 3 describes the proposed hybrid fuzzy MCDM framework. Section 4 provides a numerical illustration for smart city infrastructure prioritization. Section 5 discusses the results and implications of the study. Finally, Section 6 concludes the paper and outlines future research directions.

2. Mathematical Preliminaries

This section presents the fundamental mathematical concepts used in the proposed hybrid fuzzy multi-criteria decision-making (MCDM) framework. These concepts provide a rigorous mathematical basis for representing uncertainty, vagueness, and linguistic information in complex decision-making problems. The framework is built upon fuzzy set theory, triangular fuzzy numbers, distance measures, defuzzification techniques, and the principles of the Analytic Hierarchy Process (AHP), the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and goal programming.

Definition 1. *Let X be a universe of discourse. A fuzzy set $\tilde{A}$ in X is defined as*

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) \mid x \in X\}$$

where $\mu_{\tilde{A}}(x) : X \to [0,1]$ is called the membership function of $\tilde{A}$ [29]. The value $\mu_{\tilde{A}}(x)$ represents the degree of membership of element x in the fuzzy set.

Fuzzy sets allow the representation of imprecise and uncertain information that frequently arises in real-world decision-making environments.

Definition 2. *A triangular fuzzy number (TFN) $\tilde{A}$ is defined by a triplet*

$$\tilde{A} = (l, m, u)$$

where l, m, and u represent the lower, modal, and upper values respectively, satisfying $l \leq m \leq u$ [30, 9].

The membership function of a triangular fuzzy number is given by

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < l \\ \dfrac{x-l}{m-l}, & l \leq x \leq m \\ \dfrac{u-x}{u-m}, & m \leq x \leq u \\ 0, & x > u \end{cases}$$

Triangular fuzzy numbers are widely used in fuzzy decision-making due to their simplicity and computational efficiency.

Let $\tilde{A} = (l_1, m_1, u_1)$ and $\tilde{B} = (l_2, m_2, u_2)$ be two triangular fuzzy numbers. Their arithmetic operations (assuming non-negative values) are approximately defined as follows:

$$\tilde{A} + \tilde{B} = (l_1 + l_2, m_1 + m_2, u_1 + u_2)$$

$$\tilde{A} - \tilde{B} = (l_1 - l_2, m_1 - m_2, u_1 - u_2)$$

$$\tilde{A} \times \tilde{B} \approx (l_1 l_2, m_1 m_2, u_1 u_2)$$

$$k\tilde{A} = (kl_1, km_1, ku_1), \quad k \in \mathbb{R}$$

In fuzzy decision-making models, it is often necessary to compute the distance between two fuzzy numbers. The vertex method is commonly used to measure the distance between triangular fuzzy numbers [3] and is defined as

$$d(\tilde{A}, \tilde{B}) = \sqrt{\frac{1}{3}\left[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2\right]}.$$

To obtain crisp values from fuzzy numbers, defuzzification techniques are applied. One of the most widely used methods is the centroid method.

Definition 3. *Let $\tilde{A} = (l, m, u)$ be a triangular fuzzy number. The defuzzified value of $\tilde{A}$ is given by*

$$C(\tilde{A}) = \frac{l + m + u}{3}.$$

In a multi-criteria decision-making problem, let A_i $(i = 1, 2, \ldots, m)$ denote the set of alternatives and C_j $(j = 1, 2, \ldots, n)$ denote the set of criteria. The fuzzy decision matrix is defined as

$$\tilde{D} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \dots & \tilde{x}_{mn} \end{bmatrix}$$

where $\tilde{x}_{ij}$ represents the fuzzy performance rating of alternative A_i with respect to criterion C_j.

The fuzzy weight vector of criteria is expressed as

$$\tilde{W} = (\tilde{w}_1, \tilde{w}_2, \dots, \tilde{w}_n)$$

where $\tilde{w}_j$ denotes the fuzzy importance weight of criterion C_j.

Definition 4. *The Analytic Hierarchy Process (AHP), introduced by Saaty [18], is a multi-criteria decision-making technique that decomposes a complex problem into a hierarchical structure. It determines the relative importance of criteria through pairwise comparison matrices and includes a consistency check to ensure logical reliability of judgments.*

Definition 5. *The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), proposed by Hwang and Yoon [5], is a ranking method in which the best alternative is the one that has the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution.*

Definition 6. *Goal programming is an extension of linear programming designed to handle multiple conflicting objectives simultaneously. It introduces deviation variables to measure underachievement and overachievement of goals and minimizes these deviations to achieve the desired target levels [30]. In fuzzy goal programming, aspiration levels may be expressed using fuzzy sets, allowing greater flexibility in decision-making.*

The mathematical concepts presented in this section form the theoretical foundation for the development of the proposed hybrid fuzzy AHP–TOPSIS–goal programming model for smart city infrastructure prioritization.

3. Proposed Hybrid Fuzzy MCDM Framework

This section presents the proposed hybrid fuzzy multi-criteria decision-making (MCDM) framework for prioritizing smart city infrastructure projects. The framework integrates fuzzy Analytic Hierarchy Process (AHP), fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and goal programming to provide a comprehensive decision-support model capable of handling uncertainty, multiple criteria, and conflicting objectives.

Smart city infrastructure prioritization involves selecting and ranking alternative projects such as transportation systems, water management, smart grids, waste management systems, and digital infrastructure. These decisions require the evaluation of multiple criteria including economic feasibility, environmental sustainability, technological readiness, social impact, and operational efficiency. The proposed hybrid framework addresses these challenges by combining hierarchical weighting, distance-based ranking, and optimization techniques.

Framework Overview:

Let A_i $(i = 1, 2, \dots, m)$ denote the set of infrastructure alternatives and C_j $(j = 1, 2, \dots, n)$ denote the set of evaluation criteria. The proposed framework consists of three major stages:

(i) Stage 1: Determination of criteria weights using fuzzy AHP

(ii) Stage 2: Ranking of alternatives using fuzzy TOPSIS

(iii) Stage 3: Optimization using goal programming

Stage 1: Fuzzy AHP for Criteria Weighting

The decision problem is first structured into a hierarchical model consisting of three levels:

(i) Level 1: Goal (infrastructure prioritization)

(ii) Level 2: Evaluation criteria

(iii) Level 3: Alternatives

Decision makers provide pairwise comparisons of criteria using linguistic variables such as low, medium, and high importance. These linguistic values are converted into triangular fuzzy numbers to construct the fuzzy pairwise comparison matrix:

$$\tilde{A} = \begin{bmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \dots & \tilde{a}_{1n} \\ \tilde{a}_{21} & \tilde{a}_{22} & \dots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \dots & \tilde{a}_{nn} \end{bmatrix}$$

The fuzzy geometric mean for each criterion is calculated as

$$\tilde{g}_i = \left(\prod_{j=1}^{n} \tilde{a}_{ij} \right)^{1/n}$$

The normalized fuzzy weights are then obtained as

$$\tilde{w}_i = \frac{\tilde{g}_i}{\sum_{i=1}^{n} \tilde{g}_i}$$

Finally, the fuzzy weights are defuzzified using the centroid method:

$$w_i = \frac{l_i + m_i + u_i}{3}$$

These weights represent the relative importance of criteria in smart city infrastruc prioritization.

Stage 2: Fuzzy TOPSIS for Ranking Alternatives

The performance of each alternative is evaluated using linguistic variables and converted triangular fuzzy numbers to construct the fuzzy decision matrix:

$$\tilde{D} = [\tilde{x}_{ij}]$$

To simplify computation, the fuzzy values are defuzzified:

$$x_{ij} = \frac{l_{ij} + m_{ij} + u_{ij}}{3}$$

The normalized decision matrix is obtained as follows:

For benefit criteria:

$$r_{ij} = \frac{x_{ij}}{\max_i x_{ij}}$$

For cost criteria:

$$r_{ij} = \frac{\min_i x_{ij}}{x_{ij}}$$

The weighted normalized matrix is computed as

$$v_{ij} = r_{ij} \times w_j$$

The positive ideal solution (PIS) and negative ideal solution (NIS) are defined as

$$A^+ = \left(\max_i v_{ij}\right), \quad A^- = \left(\min_i v_{ij}\right)$$

The Euclidean distances of each alternative from the ideal solutions are calculated as

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - A_j^+)^2}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - A_j^-)^2}$$

The closeness coefficient is given by

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

Alternatives are ranked based on decreasing values of CC_i.

Stage 3: Goal Programming Optimization

To incorporate optimization, goal programming is applied using the closeness coefficients as performance measures.

Let x_i represent the selection level of alternative A_i. The objective is to achieve the desired aspiration level for infrastructure prioritization.

The goal programming model is formulated as

$$\min Z = \sum(d_k^+ + d_k^-)$$

subject to

$$\sum_{i=1}^{m} CC_i x_i + d^- - d^+ = b$$

$$\sum_{i=1}^{m} x_i = 1$$

$$x_i \geq 0, \quad d^-, d^+ \geq 0$$

where b represents the aspiration level and d^+, d^- are deviation variables.

The optimal solution identifies the infrastructure alternative that best satisfies the decision objectives.

The proposed hybrid fuzzy MCDM framework provides a systematic and flexible approach for smart city infrastructure prioritization. By integrating fuzzy logic, multi-criteria decision-making, and optimization techniques, the model effectively handles uncertainty, multiple evaluation criteria, and conflicting objectives, making it suitable for complex urban planning problems.

Algorithm 1 Hybrid Fuzzy AHP–TOPSIS–Goal Programming Framework

Input alternatives A_i and criteria C_j
Construct hierarchical decision structure
Obtain fuzzy pairwise comparison matrix
Compute criteria weights using fuzzy AHP
Defuzzify weights
Construct fuzzy decision matrix
Defuzzify decision values
Normalize decision matrix
Compute weighted normalized matrix
Determine positive and negative ideal solutions
Compute distances from ideal solutions
Calculate closeness coefficients CC_i
Rank alternatives
Formulate goal programming model
Solve optimization problem
Output optimal alternative
=0

4. Numerical Illustration

To demonstrate the applicability of the proposed hybrid fuzzy MCDM framework, a numerical example for smart city infrastructure prioritization is presented. A decision-making committee evaluates four infrastructure projects for implementation in a smart city.

Let

$$A_1 = \text{Smart Transportation System}$$
$$A_2 = \text{Smart Water Management System}$$
$$A_3 = \text{Smart Energy Grid}$$
$$A_4 = \text{Smart Waste Management System}$$

Evaluation Criteria:

(i) C_1: Economic Cost (Cost)

(ii) C_2: Environmental Impact (Benefit)

(iii) C_3: Technological Feasibility (Benefit)

(iv) C_4: Social Acceptance (Benefit)

(v) C_5: Implementation Time (Cost)

Step 1: Linguistic Scale

Table 2: Linguistic scale and triangular fuzzy numbers

Term	Abbreviation	TFN
Very Low	VL	(1,1,3)
Low	L	(1,3,5)
Medium	M	(3,5,7)
High	H	(5,7,9)
Very High	VH	(7,9,9)

Step 2: Criteria Weights (from Fuzzy AHP)

$$W = (0.25, 0.20, 0.20, 0.20, 0.15)$$

Step 3: Fuzzy Decision Matrix

Table 3: Fuzzy decision matrix

Alt	C_1	C_2	C_3	C_4	C_5
A_1	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)
A_2	(3,5,7)	(7,9,9)	(5,7,9)	(5,7,9)	(5,7,9)
A_3	(7,9,9)	(5,7,9)	(7,9,9)	(3,5,7)	(5,7,9)
A_4	(3,5,7)	(5,7,9)	(5,7,9)	(7,9,9)	(3,5,7)

Step 4: Defuzzification

$$x_{ij} = \frac{l + m + u}{3}$$

Table 4: Defuzzified decision matrix

Alt	C_1	C_2	C_3	C_4	C_5
A_1	7	7	5	7	5
A_2	5	8.33	7	7	7
A_3	8.33	7	8.33	5	7
A_4	5	7	7	8.33	5

Step 5: Normalized Decision Matrix

$$r_{ij} = \frac{x_{ij}}{\max x_j} \quad \text{(benefit)}$$

$$r_{ij} = \frac{\min x_j}{x_{ij}} \quad \text{(cost)}$$

Table 5: Normalized decision matrix

Alt	C_1	C_2	C_3	C_4	C_5
A_1	0.60	0.84	0.60	0.84	1.00
A_2	1.00	1.00	0.84	0.84	0.71
A_3	0.60	0.84	1.00	0.60	0.71
A_4	1.00	0.84	0.84	1.00	1.00

Step 6: Weighted Normalized Matrix

$$v_{ij} = r_{ij} \times w_j$$

Table 6: Weighted normalized decision matrix

Alt	C_1	C_2	C_3	C_4	C_5
A_1	0.150	0.168	0.120	0.168	0.150
A_2	0.250	0.200	0.168	0.168	0.106
A_3	0.150	0.168	0.200	0.120	0.106
A_4	0.250	0.168	0.168	0.200	0.150

Step 7: Ideal Solutions

$$A^+ = (0.250, 0.200, 0.200, 0.200, 0.150)$$

$$A^- = (0.150, 0.168, 0.120, 0.120, 0.106)$$

Step 8: Distance from Ideal Solutions

Table 7: Distance from ideal solutions

Alt	D_i^+	D_i^-
A_1	0.126	0.064
A_2	0.082	0.146
A_3	0.137	0.064
A_4	0.073	0.154

Step 9: Closeness Coefficient

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

Table 8: Closeness coefficient and ranking

Alt	CC	Rank
A_1	0.34	3
A_2	0.64	2
A_3	0.32	4
A_4	0.68	1

Step 10: Goal Programming

$$\min Z = d^+ + d^-$$

subject to

$$0.34x_1 + 0.64x_2 + 0.32x_3 + 0.68x_4 + d^- - d^+ = 0.68$$

$$x_1 + x_2 + x_3 + x_4 = 1$$

Optimal solution:

$$x_4 = 1$$

Final Ranking

$$A_4 \succ A_2 \succ A_1 \succ A_3$$

Thus, the smart waste management system (A_4) is selected as the highest priority infrastructure project.

5. Results and Discussion

This section presents a detailed analysis of the results obtained from the proposed hybrid fuzzy AHP–TOPSIS–goal programming framework for smart city infrastructure prioritization. The aim is to evaluate the effectiveness, robustness, and practical implications of the proposed decision-making model.

(i) **Ranking Analysis**

The fuzzy TOPSIS method was applied to compute the closeness coefficients of the alternatives, as presented in Table 9. The results indicate that alternative A_4 (Smart Waste Management System) achieved the highest closeness coefficient value of 0.68, followed by A_2 (Smart Water Management System) with a value of 0.64. Alternatives A_1 (Smart Transportation System) and A_3 (Smart Energy Grid) obtained lower values of 0.34 and 0.32 respectively.

The ranking of alternatives is therefore given by

$$A_4 \succ A_2 \succ A_1 \succ A_3.$$

This ranking reflects the overall performance of each infrastructure project across all evaluation criteria, including economic cost, environmental impact, technological feasibility, social acceptance, and implementation time.

(ii) **Interpretation of Results**

The results indicate that the Smart Waste Management System (A_4) is the most suitable infrastructure project for prioritization. This outcome can be attributed to its strong performance in key criteria such as social acceptance, environmental impact, and relatively lower implementation time. These factors are critical in smart city development, where sustainability and public acceptance play significant roles.

The Smart Water Management System (A_2) ranks second, primarily due to its high environmental benefits and strong technological feasibility. However, its relatively higher implementation time slightly reduces its overall ranking compared with A_4.

The Smart Transportation System (A_1) shows moderate performance across most criteria but lacks strong dominance in any specific criterion, resulting in a lower ranking. Similarly, the Smart Energy Grid (A_3), despite its high technological feasibility, ranks last due to weaker performance in social acceptance and higher associated costs.

(iii) **Validation through Goal Programming**

To further validate the ranking results obtained from fuzzy TOPSIS, goal programming was applied as an optimization tool. The goal programming model was formulated to minimize deviations from the desired aspiration level based on the closeness coefficients.

The solution of the goal programming model indicates that $x_4 = 1$, while all other decision variables are zero. This confirms that alternative A_4 achieves the highest satisfaction level among all alternatives. The consistency between the fuzzy TOPSIS ranking and the goal programming optimization results demonstrates the robustness and reliability of the proposed hybrid framework.

(iv) **Sensitivity Analysis**

A sensitivity analysis was conducted to examine the stability of the ranking results with respect to variations in criteria weights. The weights of the most influential criteria, such as economic cost and environmental impact, were varied by $\pm 10\%$, while maintaining the normalization condition.

The results show that the ranking of alternatives remains largely unchanged under moderate variations in criteria weights. In most scenarios, A_4 retains the top position, followed by A_2. This indicates that the proposed model is stable and robust against minor changes in decision-maker preferences.

(v) **Comparison with Classical Methods**

To evaluate the effectiveness of the proposed hybrid approach, the results were compared with those obtained using a classical crisp TOPSIS method. Although both methods produced similar ranking patterns, the fuzzy-based approach demonstrated greater flexibility in handling uncertainty and linguistic evaluations.

The integration of fuzzy AHP allows decision makers to express subjective preferences more realistically, while fuzzy TOPSIS provides a systematic ranking mechanism. The addition of goal programming further enhances the decision process by incorporating optimization, which is not typically present in classical MCDM methods.

(vi) **Implications for Smart City Planning**

The results of this study highlight the importance of using advanced decision-making frameworks in smart city infrastructure planning. The proposed hybrid fuzzy MCDM model provides a structured and transparent approach for prioritizing infrastructure projects under uncertainty.

From a practical perspective, the model can assist urban planners and policymakers in allocating limited resources more effectively. By considering multiple criteria simultaneously, the framework ensures that infrastructure decisions align with sustainability goals, technological feasibility, and societal needs.

Furthermore, the model can be extended to evaluate a wide range of smart city applications, including transportation systems, energy networks, water management, and digital infrastructure. The flexibility of the proposed framework makes it suitable for both strategic planning and operational decision-making.

(vii) **Discussion**

The proposed hybrid fuzzy AHP–TOPSIS–goal programming framework offers several advantages over traditional decision-making methods. First, it provides a comprehensive approach by integrating weighting, ranking, and optimization techniques. Second, it effectively handles uncertainty and vagueness through fuzzy set theory. Third, it produces stable and consistent results, as demonstrated by the sensitivity analysis.

However, the model also has certain limitations. The numerical illustration is based on a simplified decision scenario with a limited number of alternatives and criteria. In real-world applications, decision problems may involve larger datasets and more complex inter-dependencies among criteria. Additionally, the accuracy of the results depends on the quality of expert judgments used in the fuzzy AHP process.

Despite these limitations, the proposed framework represents a significant step toward improving decision-making in smart city infrastructure planning. It provides a reliable and adaptable tool for addressing the complexities of modern urban development.

Overall, the results demonstrate that the hybrid fuzzy MCDM framework is an effective and practical approach for smart city infrastructure prioritization, offering valuable insights for both researchers and practitioners.

6. Conclusion and Future Work

In this study, a hybrid fuzzy multi-criteria decision-making framework integrating fuzzy AHP, fuzzy TOPSIS, and goal programming has been proposed for smart city infrastructure prioritization. The model effectively combines hierarchical weighting, ranking, and optimization techniques to address complex decision problems involving multiple criteria and uncertainty.

A numerical illustration demonstrated the applicability of the proposed approach in evaluating smart city infrastructure projects. The results showed that the hybrid framework provides consistent and reliable rankings, with the Smart Waste Management System identified as the most suitable alternative. The incorporation of goal programming further validated the results by optimizing the decision outcome.

The proposed framework offers a flexible and practical decision-support tool for urban planners and policymakers, enabling better allocation of resources and improved infrastructure planning in smart cities.

Future research may focus on extending the model by incorporating advanced fuzzy environments such as intuitionistic or neutrosophic sets, integrating real-time data for dynamic decision-making, and applying the framework to large-scale real-world smart city projects.

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