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Selection of Appropriate UAV-Integrated with Mobile Edge Computing for Ensuring Safety and Security of Smart Cities

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Abstract

Recently, unmanned aerial vehicles (UAVs), commonly known as drones, have gained popularity due to their unique capabilities. Mobile edge computing (MEC) has emerged as a key platform for many smart systems, primarily because it offers lower latency compared to centralized cloud computing. As a result, the integration of UAVs with MEC has become essential and is increasingly utilized across various sectors, particularly in enhancing the safety and security of smart cities. A robust safety and security system, along with effective crowd control, are critical concerns for smart cities. The integration of Unmanned Aerial Vehicles (UAVs) with MEC significantly improves the safety and security of these urban environments. This research focuses on selecting the most suitable UAVs integrated with mobile edge computing to enhance the protection and safety of smart cities. Given the numerous options available, we employed the multi-criteria decision-making (MCDM) method to facilitate the selection of the appropriate UAV. A detailed explanation of the Interval-Valued Neutrosophic MEREC-EDAS method is given, highlighting the use of neutrosophic data to effectively represent uncertain and ambiguous information in decision-making. To illustrate the application of the Interval-Valued Neutrosophic MEREC-EDAS method, a case study assessing the optimal UAV for safety and security in smart cities is presented. The case study illustrates the viability and efficacy of the suggested assessment procedure. Furthermore, we carried out weighted and sensitivity analyses of the alternatives. For comparisons, we also utilized the OWCM, ENTROPY, WENSLO, CRITIC, RAM, MARICA and ARAS methods. We believe this study will assist local authorities in taking corrective action to foster community growth.

Keywords: UAV; MEC; Neutrosophic; Smart Cities; MEREC; EDAS.

1 | Introduction

The use of mobile computing at the edge has recently increased. This approach allows for real-time processing and analysis of the vast amounts of data generated by edge devices, rather than simply storing it. By doing so, organizations can gain insights and take action more quickly, effectively enhancing the capabilities of their edge network infrastructure. Mobile Edge Computing (MEC) reduces the distance within cloud networks between points of data production, collection, and analysis. Mobile edge clouds store and process data close to wireless devices within the cloud network.

The use of the Internet of Things (IoT) has seen significant growth recently across various applications, thanks to the advantages and benefits it offers. As a result, the number of connected devices is expected to increase each year [1]. Unmanned aerial vehicles (UAVs) are particularly valuable in the IoT landscape, as they possess unique features and numerous characteristics that make their integration into wireless network

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communications essential for maximizing their potential. The integration of unmanned aerial vehicles (UAVs) with mobile edge computing has greatly enhanced data processing, analysis, and communication [2]. By shifting workloads from centralized cloud servers to edge devices on these UAVs, mobile edge computing leverages their agility and flexibility. This method brings computational resources closer to the data source, which improves real-time decision-making.

UAVs (Unmanned Aerial Vehicles) equipped with edge computing capabilities can capture data from various sensors and process it in real time at or near the point of origin. These UAVs can be fitted with a range of sensors, such as cameras and infrared sensors, to gather data for navigation and specific use cases. The collected data can then be streamed to local compute facilities for applications requiring greater processing power. The integration of local edge compute racks enables near real-time analysis, facilitating fast decision-making in action. For instance, one solution provider we spoke to is using edge-enabled UAVs for customer delivery. They utilize precision location services to deliver packages to drop-off zones close to the end customer [3, 4].

Many sectors can benefit from incorporating edge-enabled UAVs into their operations, which can provide advantages such as increased productivity, enhanced operational visibility, improved decision-making, and better resource allocation. Smart cities and their safety represent a sector with significant potential for effectively utilizing edge-enabled UAVs (unmanned aerial vehicles). The emergence of fifth-generation technology allows for the creation of networks that facilitate high-speed communication between devices. In smart cities, drones equipped with Mobile Edge Computing (MEC) technology can function as airborne communication hubs, enhancing overall connectivity and efficiency.

UAVs integrated with MEC will play a crucial role in the development of smart cities. The smart city concept relies on integrating information and communication technology (ICT) and its emerging trends. UAVs have a variety of applications in smart cities, where they are easy to deploy and flexible when performing challenging tasks. Smart traffic management, which is the key to a smart city, UAVs can monitor traffic from the sky and provide real-time updates to police on the ground, enhancing smart traffic management. This is essential for any smart city and addresses a critical issue for urban areas, helping to save time and resources [5, 6]. Effective crowd management and a robust safety and security system are vital concerns for smart cities. Unmanned Aerial Vehicles (UAVs) are playing a key role in enhancing smart policing. By integrating mobile applications, wireless networks, and forensic mapping software, UAVs are helping make smart cities safer [7]. Smart transportation, UAVs (Unmanned Aerial Vehicles) have significant potential in infrastructure projects. They can be used to map sites for various developments, including metro projects and bicycle paths. UAVs offer flexibility, enabling surveyors to efficiently map long corridors. And public space security, as well as any other area that could benefit from an aerial system capable of performing complex missions remotely. This solution addresses the increasing demand for enhanced surveillance, security, and overall city protection by utilizing optical or infrared cameras to detect and report violations in real-time. It also improves the frequency and effectiveness of patrols during both day and night. All of the above demonstrates the significant role and contributions of UAVs in smart cities. With the variety of UAVs integrated with MEC for enhancing the safety and security of smart cities, it is crucial to establish effective methods for selecting the most appropriate UAV. The aim of our study is to identify which UAV is best suited for use in smart city safety and security by employing a multi-criteria decision-making (MCDM) approach.

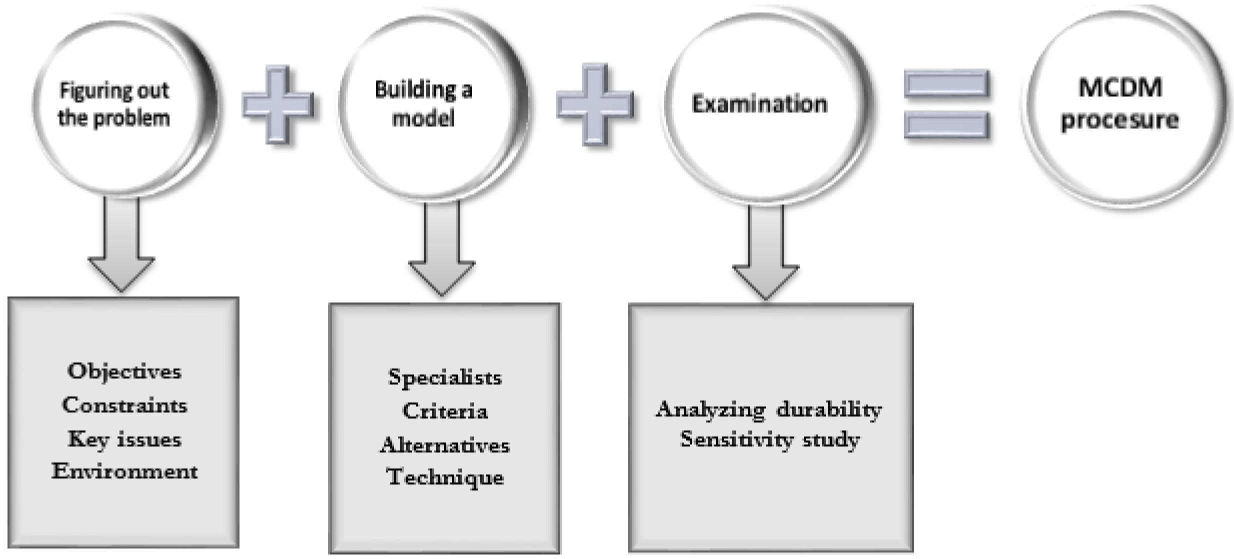

Figure 1. The explanation of the MCDM procedure.

The primary goal of multiple criteria decision making (MCDM) is to formally define and resolve choice problems. Most MCDM approaches involve openly evaluating trade-offs between different criteria and balancing them effectively. MCDM aims to minimize biases by reducing decision-makers' reliance on intuition and their vulnerability to collective decision-making errors, such as "groupthink." By using MCDM, decision-making can be improved [8]. In MCDM methods, significant attributes of alternative choices are prioritized over those that are less important. Figure 1 illustrates the Multi-Criteria Decision-Making (MCDM) procedure. The MCDM approaches for determining criteria weights are divided into three categories, as demonstrated in Figure 2. Various Multi-Criteria Decision-Making (MCDM) methods have been utilized to improve and maintain smart cities, with the TOPSIS being the most prevalent. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method has been combined with the Analytic Network Process (ANP) to evaluate the fundamental dimensions necessary for the sustainability of smart cities [9]. The AHP method was utilized to assess the strategies employed in disaster management for smart cities, addressing both natural and human-made threats, to safeguard them against extreme weather events and cyber-attacks [10]. The MEREC method falls under the objective weighting techniques used to determine criteria weights. MEREC determines criteria weights by calculating the impact of removing each criterion on the performance of alternatives. The criteria that have a greater impact on performance are given more weight [11]. The MEREC method is used to tackle the challenges faced by smart cities [12, 13].

The value of multi-criteria decision-making (MCDM) technologies in arriving at informed and definitive conclusions has been demonstrated in previous research. To tackle the ambiguity involved in evaluating and selecting the most suitable UAV for safety and security in smart cities, we propose a new MCDM model integrated with the neutrosophic set. Therefore, we will utilize the IVN-MEREC method to calculate the criteria weight and the IVN-EDAS method to rank the alternatives. The EDAS (Evaluation Based on Distance from Average Solution) method was proposed by Keshavarz Ghorabaee, M., et al.in 2015 [14]. The EDAS depends on the average solution for evaluating alternatives by considering two measures: positive distance from average and negative distance from average. In this study, interval single neutrosophic numbers are used during the EDAS procedure, referred to as the IVN-EDAS method. The IVN-EDAS method ranks UAVs integrated with MEC to select the most suitable ones for safety and security scenarios in smart cities.

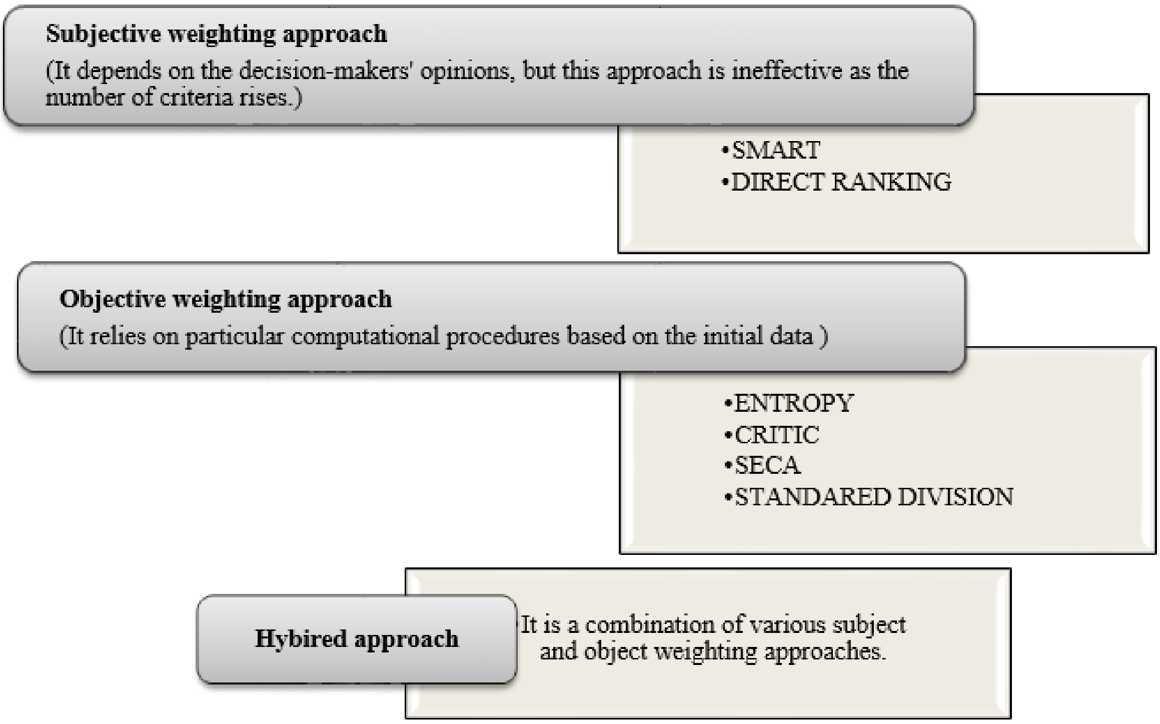

Figure 2. The categories of MCDM approaches for determining criteria weights.

We present several contributions to the literature based on the findings obtained within the scope of this study and the proposed methodology. The main contributions are summarized as follows:

- To solve the ambiguous information that frequently comes up in the decision-making process, the MEREC (Method based on Removal Effects of Criteria) method is applied to determine the weight of criteria related to UAVs used for smart city safety and security. This method is integrated with the neutrosophic set that deals with the concepts of truth, falsity, and indeterminacy (T, I, and F).
- Apply EDAS method integrated with the neutrosophic framework to rank the alternatives.
- We have designed a new scale for interval-valued neutrosophic numbers.
- Our approach helps create an accurate decision matrix by addressing the imprecision and lack of information in real decision-making processes.
- A sensitivity analysis was conducted in order to assess and determine the stability of the proposed method under various sets of criteria weights.
- The proposed strategy was compared to different MCDM methods, including newly and commonly used ones, and the results showed the effectiveness of our strategy.

The rest of the paper is structured as follows: Section 2: Related Work, Section 3: Methodology, Section 4: Case Study & Analysis, Section 5: Sensitivity Analysis, Section 6: Comparative Analysis, Section 7: Managerial Implications and Section 8: Conclusion & Future Work.

2 | Related Work

In terms of network speed, distributed systems outperform centralized systems. This is a result of the data not being kept in one central location. Long wait times and system slowness can result from a big number of users attempting to contact a server that is overloaded in centralized systems. Decentralized architecture, on the other hand, can lessen these problems. In order to process data, improve IoT services, and handle technical issues pertaining to security, privacy, and computer vision, cutting-edge edge artificial intelligence is being incorporated into UAVs. To enhance data processing, improve IoT services, and address technical issues related to security, privacy, and computer vision, edge artificial intelligence is being integrated into UAVs [15].

Cameras installed on unmanned aerial vehicles (UAVs) capture large volumes of visual data that need to be analyzed quickly for efficient decision-making. However, there are often significant delays when transmitting this data from UAVs to cloud servers. Additionally, deploying numerous IoT devices, such as UAVs, can strain security, reliability, and bandwidth. Therefore, processing data at the network edge can lead to faster response times, more effective processing, and reduced pressure on the network overall [16, 17].

UAVs are being used as platforms to provide reliable communications, addressing the limitations of traditional cloud computing [18]. Unmanned Aerial Vehicles (UAVs) can serve various purposes in delivering edge computing services. UAVs can function in several roles: they can act as mobile devices, MEC servers, or relays. By shifting their computational tasks to a MEC server, UAVs can operate as mobile gadgets, monitor a network of mobile endpoints, or facilitate communication between mobile end nodes and a MEC server [19, 20]. This classification illustrates the diverse ways UAVs can enhance edge computing solutions for the Internet of Things (IoT).

UAVs are essential for the development and enhancement of smart cities through various tasks [21], including infrastructure monitoring, traffic control [22], building maintenance and optimization, health crisis management, public safety, and environmental disaster prevention [21, 22]. In addition to these tasks, there are many benefits to using UAVs in developing smart cities, namely: Improved Security through monitoring around the clock allows for swift and efficient detection of intrusions and violations, resulting in heightened awareness of risks linked to individuals and their surroundings. Efficiency in terms of cost through the Economic analysis that identifies potential damage to equipment and infrastructure reduces emergency response costs while keeping equipment operational. Figure 3 illustrates various applications of UAVs in enhancing security and safety in smart cities.

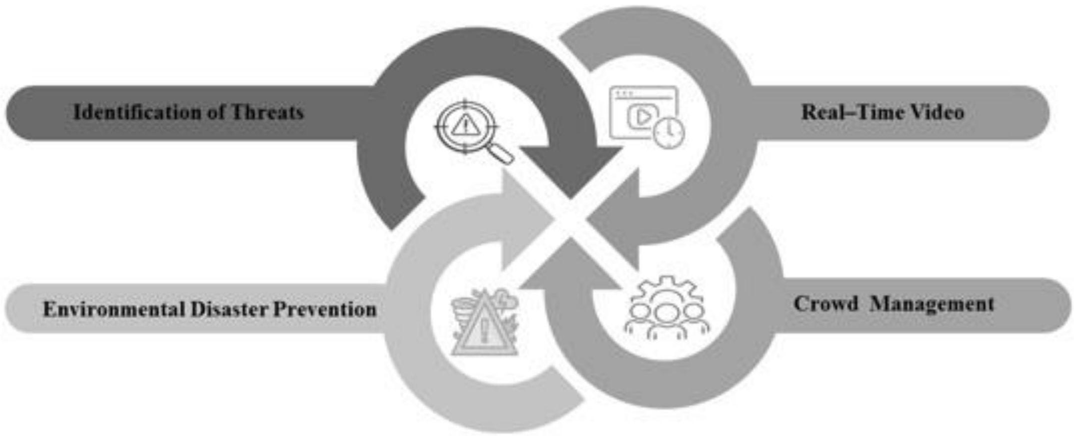

Figure 3. Applications of UAVs in Enhancing Security and Safety in Smart Cities.

3 | Methodology

This study employed two Multi-Criteria Decision Making (MCDM) techniques, combined with a neutrosophic environment, to evaluate the effectiveness of Unmanned Aerial Vehicles (UAVs) integrated with Mobile Edge Computing (MEC) for enhancing safety in smart cities. We utilized the MEREC method integrated with interval valued neutrosophic numbers as the MCDM technique to determine the weights of the criteria. The MEREC integrated with interval valued neutrosophic numbers (IVN-MEREC) to address any ambiguity in the decision-making process. Additionally, the IVN-EDAS method was applied to rank the UAVs within their respective categories based on the weights obtained from IVN-MEREC. The following steps provide a detailed explanation of the proposed approach illustrated in Figure 4.

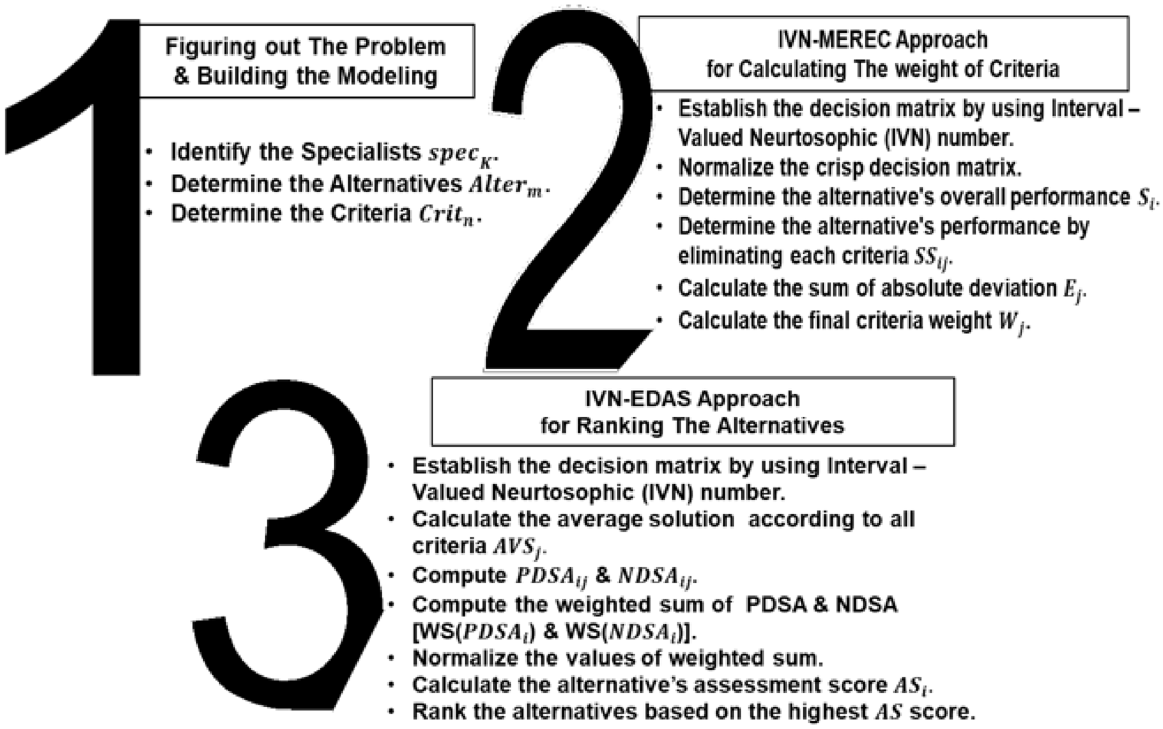

Figure 4. The steps of the proposed IVN-MEREC-EDAS approach.

Table 1. IVNs scale.

Linguistic Terms	IVN Value $< [T^L, T^U], [I^L, I^U], [F^L, F^U] >$
Extreme Insignificant (EI)	$< [0.00, 0.00], [0.80, 0.90], [1.00, 1.00] >$
Insignificant (IS)	$< [0.15, 0.25], [0.65, 0.75], [0.85, 0.95] >$
Slightly Significant (SS)	$< [0.30, 0.40], [0.60, 0.70], [0.60, 0.75] >$
Median Significant (MS)	$< [0.50, 0.50], [0.50, 0.50], [0.50, 0.50] >$
Significant (S)	$< [0.65, 0.75], [0.35, 0.45], [0.40, 0.45] >$
Very Significant (VS)	$< [0.80, 0.90], [0.20, 0.30], [0.30, 0.35] >$
Very Much Significant (VMS)	$< [0.86, 0.96], [0.10, 0.15], [0.15, 0.10] >$
Extreme Significance (ES)	$< [1.00, 1.00], [0.00, 0.00], [0.00, 0.00] >$

Step 1. Figuring out the problem and Building the modeling

We are tackling the problem as a multi-criteria decision-making issue. To identify the optimal choice for a specific scenario, a team of specialist $Spec = \{spec1, spec2 \dots spec_k\}$will evaluate a set of alternatives $Alter = \{Alter1, \dots \dots Alter_m\}$based on a defined set of features or criteria $Crit = \{Crit1, Crit2, \dots \dots Crit_n\}$. This process is similar to how any multi-criteria decision-making problem is approached.

Step 2. IVN-MEREC for calculating the weight of criteria.

The MEREC method focuses on the elimination effects of criteria and is recognized as one of the objective weighting methods. In this approach, criteria that significantly impact performance are assigned greater weights. Although the MEREC method is easy to implement, it fails to account for the ambiguity and uncertainty often present in real-life decision-making.

To address this limitation, we have developed a novel version of the MEREC method that incorporates neutrosophic sets, which we call the IVNS-MEREC approach. This new method effectively manages knowledge gaps, ambiguity, and uncertainty by integrating concepts from the interval-valued neutrosophic environment for the first time. The proposed IVNS-MEREC method consists of several clearly defined steps, which are detailed below:

Step 2.1: Establish the decision matrix

Step 2.1.1: Establish linguistic decision matrices: Experts assess the criteria for each alternative using linguistic term, creating a linguistic decision matrix.

Step2.1.2: Establish the IVN decision matrix: specialists often use terms like "important" or "not important" to convey the significance of each criterion. However, these terms are vague and do not provide the level of certainty needed for proper evaluation. To address this issue, we utilize an interval-valued neutrosophic (IVN) scale, which allows for the incorporation of imprecise information in our assessments. To overcome the issues of vagueness and uncertainty, we represent the specialists' opinions using the interval-valued neutrosophic number scale, as shown in Table 1.

$$D = [\tilde{d}_{ij}]_{m,n} =$$

$$\begin{bmatrix} < [T_{11}^L, T_{11}^U], [I_{11}^L, I_{11}^U], [F_{11}^L, F_{11}^U] > & \cdots & < [T_{1j}^L, T_{1j}^U], [I_{1j}^L, I_{1j}^U], [F_{1j}^L, F_{1j}^U] > \\ \vdots & \ddots & \vdots \\ < [T_{i1}^L, T_{i1}^U], [I_{i1}^L, I_{i1}^U], [F_{i1}^L, F_{i1}^U] > & \cdots & < [T_{mn}^L, T_{mn}^U], [I_{mn}^L, I_{mn}^U], [F_{mn}^L, F_{mn}^U] > \end{bmatrix} \quad (1)$$

Where, m is the number of alternatives$(Alter)$, n is the number of criteria $(Crit)$ and $(\tilde{d}_{ij})$ is the IVN value of the ith alternative with respect to the jth criterion.

Step 2.1.3: Aggregated the IVN decision matrices: Each specialist will have their own IVN decision matrix, as there are several specialists involved. To combine these individual matrices into a comprehensive matrix, we must use the IVN aggregation decision matrix $(IVN - agg_{ij})$, that obtained by utilizing the aggregated equation and the addition operation on the IVN as follows:

$$IVN - agg_{ij} = \frac{\sum_{j=1}^{K} \tilde{d}_{ij}}{K} \quad (2)$$

$$Z_1 + Z_2 + Z3 = \{[T_1^L + T_2^L + T_3^L - T_1^L T_2^L T_3^L,\ T_1^U + T_2^U + T_3^U - T_1^U T_2^U T_3^U], [I_1^L I_2^L I_3^L, I_1^U I_2^U I_3^U], [F_1^L F_2^L F_3^L, F_1^U F_2^U F_3^U]\} \quad (3)$$

Where, $Z_1 = \{[T_1^L, T_1^U], [I_1^L, I_1^U], [F_1^L, F_1^U]\}$, $Z_2 = \{[T_2^L, T_2^U], [I_2^L, I_2^U], [F_2^L, F_2^U]\}$ and $Z_3 = \{[T_3^L, T_3^U], [I_3^L, I_3^U], [F_3^L, F_3^U]\}$ be three neutrosophic numbers with interval values.

Step 2.1.4: Establish the crisp aggregation matrix: Translates linguistic concepts into numerical values that indicate the degree of confidence in the specialist's judgment using the scoring function that calculates as follows:

$$score(A) = \left(\frac{1}{4}\right) \times [2 + T^L + T^U - 2I^L - 2I^U - F^L - F^U] \quad (4)$$

Step 2.2: Normalize the crisp decision matrix, as follows:

$$n_{ij}^x = \begin{cases} \frac{\min x_{kj}}{x_{ij}} & if\ j \in beneficial \\ \frac{x_{ij}}{\max x_{kj}} & if\ j \in non - beneficial \end{cases} \quad (5)$$

Step 2.3: Determine the alternatives' overall performanceS_i. In this stage, the overall performance of the alternatives is assessed using a logarithmic measure with equal criteria weights. A non-linear function forms the basis for this assessment. S_i is calculated as follows:

$$s_i = \ln(1 + (\frac{1}{m} \sum_j |\ln(n_{ij}^x)|)) \quad (6)$$

Step 2.4: Determine the alternatives' performance by eliminating each criterion.

Using a logarithmic measure is similar to the previous step. However, in this stage, we analyze each criterion individually to evaluate the performance of each alternative. This means that m criteria correspond to sets of m performance evaluations. We denote the overall performance of the ith alternative with respect to the elimination of the jth criterion as SS_{ij} this notation shows how well the ith alternative performed when the jth criterion was eliminated. The following equation will be used for the calculations in this step:

$$ss_{ij} = \ln(1 + (\frac{1}{m} \sum_{k,k\neq j}\left|\ln\left(n_{ij}^{x}\right)\right|)) \tag{7}$$

Step 2.5: Calculate the sum of the absolute deviations, as follows:

$$E_j \ = \ \sum_i\left|ss_{ij} - s_i \ \right| \tag{8}$$

Step 2.6: Establish the criteria's final weights.

The elimination effects E_j from the previous step are used to objectively determine each criterion's weight. The letter w_j stands for the weight of the jth criterion. The following formula is used to determinew_j:

$$w_j = \frac{E_j}{\sum_k E_k} \tag{9}$$

Step 3: IVN-EDAS for rank the alternatives

Step 3.1: Establish the decision matrix

We frequently encounter ambiguity when making decisions since they typically entail information that is confusing or uncertain. But addressing uncertainty with language factors alone is not enough. Since neutrosophic can handle the ambiguous information that frequently comes up in decision-making, we employed it to address linguistic ambiguity. Using the phrases used by experts to construct decision matrices, we translate the linguistic information into a matching numerical scale using the interval-valued neutrosophic scale (IVNs), as shown in Table 1.

Step 3.1.1: Establish linguistic decision matrices

Step 3.1.2: Establish the IVN decision matrix, utilizing Eq. (1).

Step 3.1.3: Aggregated the IVN decision matrices, utilizing Eqs. (2) and (3).

Step 3.1.4: Establish the crisp aggregation matrix, utilizing Eq. (4).

Step 3.2: Calculate the average solution (AVS) according to all criteria, as follows:

$$AVS_j = \frac{\sum_{i=1}^{n} x_{ij}}{m} \tag{10}$$

$$AVS = \left[AVS_j\right]_{1xm} \tag{11}$$

Step 3.3: Compute the positive distance from average (PDSA) and negative distance from average (NDSA) matrices as follows:

$$PDSA = \left[PDSA_{ij}\right]_{nxm} = \begin{cases} \frac{\max(0,(x_{ij}-AVS_j))}{AVS_j} for\ beneficial\ criteria \\ \frac{\max(0,(AVS_j-x_{ij}))}{AVS_j}\ for\ non-beneficial\ criteria \end{cases} \tag{12}$$

$$NDSA = \left[NDSA_{ij}\right]_{nxm} = \begin{cases} \frac{\max(0,(AVS_j-x_{ij}))}{AVS_j} for\ beneficial\ criteria \\ \frac{\max(0,(x_{ij}-AVS_j))}{AVS_j}\ for\ non-beneficial\ criteria \end{cases} \tag{13}$$

Step 3.4: Compute the weighted sum of PDSA & NDSA for all alternatives, as follows:

$$WS(PDSA)_i = \sum_{j=1}^{n} W_j . PDSA_{ij} \tag{14}$$

$$WS(NDSA)_i = \sum_{j=1}^{n} W_j . NDSA_{ij} \tag{15}$$

Where, W_j represents the jth criterion's weight

Step 3.5: Normalize the values of $WS(PDSA)$ and $WS(NDSA)$ for all alternatives, as follows:

$$Norm\ (PDSA)_i = \frac{WS(PDSA)_i}{max_i(WS(PDSA)_i)} \tag{16}$$

$$Norm\ (NDSA)_i = 1 - \frac{WS(NDSA)_i}{max_i(WS(NDSA)_i)} \tag{17}$$

Step 3.6: Determine each alternative's assessment score (AS), as follows:

$$AS_i = \frac{1}{2}(Norm\ (PDSA)_i + Norm\ (NDSA)_i),\ where\ 0 \le AS_i \le 1 \tag{18}$$

Step 3.7: Rank the alternatives:

The alternative with the highest AS value is considered the optimal alternative.

4 | Case Study and Analysis

Oslo, a smart city, aims to create an eco-friendly and sustainable environment. While there are distinctions between smart cities and sustainable cities, they often share similar objectives. It's important to note that a city can be sustainable without being considered smart; however, Oslo exemplifies both qualities. With a population of 670,000 residents, Oslo has made a significant commitment to sustainability and the integration of smart technology, putting them on a path to achieve their goals. The city is also focused on enhancing safety and security by monitoring roadways and crowds, capturing real-time video, and identifying potential threats.

This section presents a case study on selecting a suitable UAV for the safety and security of Oslo's smart city using proposed IVN-MEREC-EDAS approach. Four alternatives $Alter1, Alter2, Alter3, and\ Alter4$ shown in Figure 4 were evaluated by a group of three highly knowledgeable specialists in the field, as detailed in Table 2, based on the five criteria outlined in Table 3.

Table 2. Details about specialists.

Specialist	Degree	Field
$Spec1$	PhD	Designer Engineering
$Spec2$	PhD	Mechanical Engineering
$Spec3$	M.Sc.	Communications Engineering

Table 3. Criteria for evaluation & its type.

ID	Criteria	Abbreviation	Type
$Crit1$	Real-time video streaming	is a crucial criterion that includes the following components: • Low Latency: Minimizing delays in the video feed is essential for timely decision-making. • Encrypted Signal: Implementing encryption helps prevent unauthorized access and ensures the privacy of the operations.	max

		• Extended Transmission Range: in certain situations, a longer transmission range may be necessary to support extended flights, such as those conducted for search and rescue missions or disaster relief efforts.	
$Crit2$	Flight Time	Long-lasting batteries provide extended flight durations, enabling continuous observation while reducing the need for frequent landings and battery replacements.	max
$Crit3$	High resolution camera	Including visual and thermal imaging, enhance situational awareness by providing clear, detailed views of scenes. Thermal imaging is crucial for nighttime operations, as it detects heat signatures and is particularly helpful during search and rescue missions.	max
$Crit4$	Safety	Includes the following components: • 360-Degree Detection: UAVs should have comprehensive detection capabilities and additional features to avoid obstacles effectively. They must be able to navigate complex environments securely. • Autonomy: Some level of autonomy is beneficial to ensure that the drone can continue flying even if the pilot becomes distracted by events on the ground. • Return to Home (RTH): this feature ensures that the UAV can safely return to its starting position in cases of low battery or communication failure. • Geofencing : This allows operators to set boundaries, ensuring that the drone remains within a designated area.	max
$Crit5$	Durability	Ability to operate in various weather conditions, such as strong winds, rain, and extreme temperatures. Additionally, self-correcting systems, often referred to as Turtle Mode, can help ensure the drone can recover from potential crashes or collisions.	max

Table 4. Alternatives.

Alternatives	Model	Description
***Alter*1**	**DJI Matrice 30**	DJI's Matrice series is popular among law enforcement and public safety agencies. The M30 model can be equipped with an optional thermal camera and is designed to be rugged and portable, making it suitable for fieldwork, including public safety operations: • Flight Time: 41 minutes with the self-heating TB30 battery. • Camera: 48MP 1/2" CMOS zoom camera featuring 5x to 16x optical zoom and 200x digital zoom, capable of capturing 8K photos and recording 4K video at 30fps. • Laser Rangefinder: Delivers precise positional information for objects up to 0.75 miles (1.2 km) away. • Thermal Camera (M30T only): 640x512 radiometric thermal camera, crucial for low-light public safety operations. • Weather Resistance: IP55 ingress protection; operational in temperatures ranging from -4°F to 122°F. • Portability: Foldable and lightweight, with a take-off weight of 8 pounds, enhancing its portability. • Safety Features: Includes a low-light first-person pilot camera, built-in redundancy and backup processes, a three-propeller emergency landing system, a Health Management System, and six-way collision avoidance sensors.
***Alter*2**	**DJI Matrice 300 RTK**	The Matrice 300 RTK is an earlier and larger model in the Matrice series. Equipped with RTK technology, it enables high-accuracy mapping for precise data collection, making the M300 an excellent choice for public safety organizations looking to perform 3D mapping. This capability is particularly useful for creating detailed 2D and 3D representations of crime scenes or traffic accidents. Additionally, the drone is effective for long-range operations, such as searching for missing persons or surveying active wildfires: • Flight Time: 55 minutes • Camera: H20T with a 20 MP Zoom (up to 200x max zoom and 4K video), a 12 MP Wide lens, and a 640×512 resolution thermal camera. • Speed: Up to 51 mph • Weather Resistance: IP45 weather sealing rating • Payload Capacity Can mount up to three payloads simultaneously • Transmission Range: Triple-channel 1080p video transmission at 30 fps, with a range of up to 9.3 miles (15 km) • Data Security: AES-256 encryption

		• Safety Features: Anti-collision beacon, obstacle detection sensors, and an ADS-B receiver
***Alter*3**	DJI Mavic 3T	• Flight Time: 45 minutes. • Cameras: Equipped with dual visual and thermal cameras. The visual camera features a 48 MP sensor, while the thermal camera provides 640 x 512 pixels of radiometric data. • Transmission Range: Utilizes the O3 Enterprise transmission system, allowing for a maximum control distance of 9 miles (15 km) and high-definition 1080p live broadcasting at 30 frames per second. • Safety Features: Includes wide-angle vision sensors on all sides, adjustable braking distances, proximity warnings, APAS 5.0, and an advanced Return-to-Home (RTH) function. • Data Protection: Offers a local data mode, the option to delete all collected data, and AES-256 bit encryption for secure data transmission.
***Alter*4**	BRINC's Lemur 2	• Flight Time: 31 minutes. • Two-Way Communication: During hostage crises or active shooter occurrences, this function enables law enforcement to communicate with victims who are being held prisoner and negotiate with suspects. • Glass Breaker: One of the unique blades in the Lemur 2 is made specifically for busting through windows to enter buildings. • Night Vision Sensor: operate effectively in low-light conditions. • Encrypted Video Signal: Ensures the secure transmission of video data.

Step 1: Oslo is a smart city that seeks to enhance security and safety through the use of Unmanned Aerial Vehicles (UAVs). With a wide variety of UAVs available, we encounter challenges in multi-criteria decision-making. To assist decision-makers in making informed choices, we propose the IVN-MEREC-EDAS method. In Table 2, we describe three specialists in this field. The Table 3 outlines a select set of evaluation criteria, while the Table 4 presents four alternatives for consideration in selecting the best UAV option.

Step 2. Establish the criteria weights by adhering to the stages outlined in the IVN-MEREC approach. First, construct the three linguistic decision matrices, as we have three specialists, as shown in Tables 5, 6, and 7. Then, construct the three IVN decision matrices using interval-valued neutrosophic scales as shown in Tables 8, 9, and 10. Three views have been formed regarding the professional evaluation criteria. Therefore, all three IVN decision matrices must be combined into an aggregated one called the IVN aggregation decision matrix ($IVN - agg_{ij}$) by applying Eq. (2) and using the addition operation on the IVN, as specified in Eq. (3), as shown in Table 11. Subsequently, we transform the IVN-aggregated decision matrix into a CRISP decision matrix using the scoring function outlined in Eq. (4), as shown in Table 12. This process yields the final decision matrix.

Then, the final decision matrix (crisp) is normalized by applying Eq. (5), resulting in the normalized decision matrix as illustrated in Table 13. Decision-makers should assess the overall performance of the alternatives

(s_i). They compute these values using Eq. (6), as illustrate in Table 14. Following that, the alternatives' overall performances by removing each criterion (ss_{ij}) is calculated by utilizing Eq. (7) as shown in Table 15.

Decision-makers evaluate how removing each criterion affects the overall performance of the alternatives by applying the deviation-based formula presented in Eq. (8), along with the results from Step 2.3 and the data shown in Table 15. Next, they determine the weight of each criterion based on its impact on the alternatives' performance when it is removed. Using Eq. (9) and the values derived from the previous step, the weights are calculated and displayed in Table 16. Figure 5 presents the ranking of the criteria based on their final weights.

Table 5. First expert's linguistic decision-making matrix.

Alternatives	$Crit_1$	$Crit_2$	$Crit_3$	$Crit_4$	$Crit_5$
$Alter_1$	SS	VS	S	VS	VS
$Alter_2$	VS	VS	VMS	S	S
$Alter_3$	S	VMS	VS	VMS	VMS
$Alter_4$	MS	S	MS	SS	SS

Table 6. Second expert's linguistic decision-making matrix.

Alternatives	$Crit_1$	$Crit_2$	$Crit_3$	$Crit_4$	$Crit_5$
$Alter_1$	MS	VMS	S	VMS	VMS
$Alter_2$	S	S	VMS	MS	MS
$Alter_3$	VS	VMS	VS	VMS	VMS
$Alter_4$	MS	S	MS	MS	SS

Table 7. Third expert's linguistic decision-making matrix.

Alternatives	$Crit_1$	$Crit_2$	$Crit_3$	$Crit_4$	$Crit_5$
$Alter_1$	IS	VS	S	VS	VS
$Alter_2$	VS	VS	VMS	S	MS
$Alter_3$	S	VS	VS	VS	VS
$Alter_4$	MS	MS	SS	SS	MS

Table 8. The first expert's IVN decision matrix.

Alternatives	$Crit_1$
	$<[T^L,T^U],[I^L,I^U],[F^L,F^U]>$
$Alter_1$	$<[0.30\,,0.40],[0.60,0.70],[0.60,0.75]>$
$Alter_2$	$<[0.80\,,0.90],[0.20,0.30],[0.30,0.35]>$
$Alter_3$	$<[0.65\,,0.75],[0.35,0.45],[0.40,0.45]>$
$Alter_4$	$<[0.50\,,0.50],[0.50,0.50],[0.50,0.50]>$
Alternatives	$Crit_2$
	$<[T^L,T^U],[I^L,I^U],[F^L,F^U]>$
$Alter_1$	$<[0.80\,,0.90],[0.20,0.30],[0.30,0.35]>$
$Alter_2$	$<[0.80\,,0.90],[0.20,0.30],[0.30,0.35]>$
$Alter_3$	$<[0.86\,,0.96],[0.10,0.15],[0.15,0.20]>$
$Alter_4$	$<[0.65\,,0.75],[0.35,0.45],[0.40,0.45]>$
Alternatives	$Crit_3$
	$<[T^L,T^U],[I^L,I^U],[F^L,F^U]>$
$Alter_1$	$<[0.65\,,0.75],[0.35,0.45],[0.40,0.45]>$
$Alter_2$	$<[0.86\,,0.96],[0.10,0.15],[0.15,0.20]>$
$Alter_3$	$<[0.80\,,0.90],[0.20,0.30],[0.30,0.35]>$

Alternatives	
$\boldsymbol{Alter_4}$	$<[0.50\ ,0.50],[0.50,0.50],[0.50,0.50]>$
Alternatives	$Crit_4$
	$<[T^L,T^U],[I^L,I^U],[F^L,F^U]>$
$\boldsymbol{Alter_1}$	$<[0.86\ ,0.96],[0.10,0.15],[0.15,0.20]>$
$\boldsymbol{Alter_2}$	$<[0.50\ ,0.50],[0.50,0.50],[0.50,0.50]>$
$\boldsymbol{Alter_3}$	$<[0.86\ ,0.96],[0.10,0.15],[0.15,0.20]>$
$\boldsymbol{Alter_4}$	$<[0.50\ ,0.50],[0.50,0.50],[0.50,0.50]>$
Alternatives	$Crit_5$
	$<[T^L,T^U],[I^L,I^U],[F^L,F^U]>$
$\boldsymbol{Alter_1}$	$<[0.86\ ,0.96],[0.10,0.15],[0.15,0.20]>$
$\boldsymbol{Alter_2}$	$<[0.50\ ,0.50],[0.50,0.50],[0.50,0.50]>$
$\boldsymbol{Alter_3}$	$<[0.86\ ,0.96],[0.10,0.15],[0.15,0.20]>$
$\boldsymbol{Alter_4}$	$<[0.30\ ,0.40],[0.60,0.70],[0.60,0.75]>$

Table 9. The second expert's IVN decision matrix.

Alternatives	$\boldsymbol{Crit_1}$
	$<[T^L,T^U],[I^L,I^U],[F^L,F^U]>$
$\boldsymbol{Alter_1}$	$<[0.50\ ,0.50],[0.50,0.50],[0.50,0.50]>$
$\boldsymbol{Alter_2}$	$<[0.65\ ,0.75],[0.35,0.45],[0.40,0.45]>$
$\boldsymbol{Alter_3}$	$<[0.80\ ,0.90],[0.20,0.30],[0.30,0.35]>$
$\boldsymbol{Alter_4}$	$<[0.50\ ,0.50],[0.50,0.50],[0.50,0.50]>$
Alternatives	$Crit_2$
	$<[T^L,T^U],[I^L,I^U],[F^L,F^U]>$
$\boldsymbol{Alter_1}$	$<[0.86\ ,0.96],[0.10,0.15],[0.15,0.20]>$
$\boldsymbol{Alter_2}$	$<[0.65\ ,0.75],[0.35,0.45],[0.40,0.45]>$
$\boldsymbol{Alter_3}$	$<[0.86\ ,0.96],[0.10,0.15],[0.15,0.20]>$
$\boldsymbol{Alter_4}$	$<[0.65\ ,0.75],[0.35,0.45],[0.40,0.45]>$
Alternatives	$Crit_3$
	$<[T^L,T^U],[I^L,I^U],[F^L,F^U]>$
$\boldsymbol{Alter_1}$	$<[0.65\ ,0.75],[0.35,0.45],[0.40,0.45]>$
$\boldsymbol{Alter_2}$	$<[0.86\ ,0.96],[0.10,0.15],[0.15,0.20]>$
$\boldsymbol{Alter_3}$	$<[0.80\ ,0.90],[0.20,0.30],[0.30,0.35]>$
$\boldsymbol{Alter_4}$	$<[0.50\ ,0.50],[0.50,0.50],[0.50,0.50]>$
Alternatives	$Crit_4$
	$<[T^L,T^U],[I^L,I^U],[F^L,F^U]>$
$\boldsymbol{Alter_1}$	$<[0.80\ ,0.90],[0.20,0.30],[0.30,0.35]>$
$\boldsymbol{Alter_2}$	$<[0.65\ ,0.75],[0.35,0.45],[0.40,0.45]>$
$\boldsymbol{Alter_3}$	$<[0.86\ ,0.96],[0.10,0.15],[0.15,0.20]>$
$\boldsymbol{Alter_4}$	$<[0.30\ ,0.40],[0.60,0.70],[0.60,0.75]>$
Alternatives	$Crit_5$
	$<[T^L,T^U],[I^L,I^U],[F^L,F^U]>$
$\boldsymbol{Alter_1}$	$<[0.80\ ,0.90],[0.20,0.30],[0.30,0.35]>$
$\boldsymbol{Alter_2}$	$<[0.65\ ,0.75],[0.35,0.45],[0.40,0.45]>$
$\boldsymbol{Alter_3}$	$<[0.86\ ,0.96],[0.10,0.15],[0.15,0.20]>$
$\boldsymbol{Alter_4}$	$<[0.30\ ,0.40],[0.60,0.70],[0.60,0.75]>$

Table 10. The third expert's IVN decision matrix.

Alternatives	$Crit_1$
	$< [T^L, T^U], [I^L, I^U], [F^L, F^U] >$
$Alter_1$	$<$ [0.15 , 0.25], [0.65,0.75], [0.85,0.95] $>$
$Alter_2$	$<$ [0.80 , 0.90], [0.20,0.30], [0.30,0.35] $>$
$Alter_3$	$<$ [0.65 , 0.75], [0.35,0.45], [0.40,0.45] $>$
$Alter_4$	$<$ [0.50 , 0.50], [0.50,0.50], [0.50,0.50] $>$
Alternatives	$Crit_2$
	$< [T^L, T^U], [I^L, I^U], [F^L, F^U] >$
$Alter_1$	$<$ [0.80 , 0.90], [0.20,0.30], [0.30,0.35] $>$
$Alter_2$	$<$ [0.80 , 0.90], [0.20,0.30], [0.30,0.35] $>$
$Alter_3$	$<$ [0.80 , 0.90], [0.20,0.30], [0.30,0.35] $>$
$Alter_4$	$<$ [0.50 , 0.50], [0.50,0.50], [0.50,0.50] $>$
Alternatives	$Crit_3$
	$< [T^L, T^U], [I^L, I^U], [F^L, F^U] >$
$Alter_1$	$<$ [0.65 , 0.75], [0.35,0.45], [0.40,0.45] $>$
$Alter_2$	$<$ [0.86 , 0.96], [0.10,0.15], [0.15,0.20] $>$
$Alter_3$	$<$ [0.80 , 0.90], [0.20,0.30], [0.30,0.35] $>$
$Alter_4$	$<$ [0.30 , 0.40], [0.60,0.70], [0.60,0.75] $>$
Alternatives	$Crit_4$
	$< [T^L, T^U], [I^L, I^U], [F^L, F^U] >$
$Alter_1$	$<$ [0.80 , 0.90], [0.20,0.30], [0.30,0.35] $>$
$Alter_2$	$<$ [0.65 , 0.75], [0.35,0.45], [0.40,0.45] $>$
$Alter_3$	$<$ [0.80 , 0.90], [0.20,0.30], [0.30,0.35] $>$
$Alter_4$	$<$ [0.30 , 0.40], [0.60,0.70], [0.60,0.75] $>$
Alternatives	$Crit_5$
	$< [T^L, T^U], [I^L, I^U], [F^L, F^U] >$
$Alter_1$	$<$ [0.80 , 0.90], [0.20,0.30], [0.30,0.35] $>$
$Alter_2$	$<$ [0.50 , 0.50], [0.50,0.50], [0.50,0.50] $>$
$Alter_3$	$<$ [0.80 , 0.90], [0.20,0.30], [0.30,0.35] $>$
$Alter_4$	$<$ [0.50 , 0.50], [0.50,0.50], [0.50,0.50] $>$

Table 11. The aggregated IVN decision matrix.

Alternatives	$Crit_1$
	$< [T^L, T^U], [I^L, I^U], [F^L, F^U] >$
$Alter_1$	$<$ [0.3091 , 0.3666], [0.0650,0.0875], [0.0850,0.1187] $>$
$Alter_2$	$<$ [0.6113 , 0.6475], [0.0046,0.0135], [0.0120,0.0183] $>$
$Alter_3$	$<$ [0.5873 , 0.6312], [0.0081,0.0202], [0.0160,0.0236] $>$
$Alter_4$	$<$ [0.4583 , 0.4583], [0.0416,0.0416], [0.0416,0.0416] $>$
Alternatives	$Crit_2$
	$< [T^L, T^U], [I^L, I^U], [F^L, F^U] >$
$Alter_1$	$<$ [0.6365, 0.6608], [0.0013,0.0045], [0.0045,0.0081] $>$
$Alter_2$	$<$ [0.6113 , 0.6475], [0.0046,0.0135], [0.012,0.0183] $>$
$Alter_3$	$<$ [0.6427 , 0.6635], [0.0006,0.0022], [0.0022,0.0046] $>$
$Alter_4$	$<$ [0.5295 , 0.5729], [0.0204,0.0337], [0.0266,0.0337] $>$
Alternatives	$Crit_3$
	$< [T^L, T^U], [I^L, I^U], [F^L, F^U] >$

$\boldsymbol{Alter_1}$	$<[0.5584, 0.6093], [0.0142, 0.0303], [0.0213, 0.0303]>$
$\boldsymbol{Alter_2}$	$<[0.6479, 0.6650], [0.0003, 0.0011], [0.0011, 0.0026]>$
$\boldsymbol{Alter_3}$	$<[0.6293, 0.6570], [0.0026, 0.0090], [0.0090, 0.0142]>$
$\boldsymbol{Alter_4}$	$<[0.4083, 0.4333], [0.0500, 0.0583], [0.0500, 0.0625]>$
Alternatives	$Crit_4$
	$<[T^L, T^U], [I^L, I^U], [F^L, F^U]>$
$\boldsymbol{Alter_1}$	$<[0.6365, 0.6608], [0.0013, 0.0045], [0.0045, 0.0081]>$
$\boldsymbol{Alter_2}$	$<[0.5295, 0.5729], [0.0204, 0.0337], [0.0266, 0.0337]>$
$\boldsymbol{Alter_3}$	$<[0.6427, 0.6635], [0.0006, 0.0022], [0.0022, 0.0046]>$
$\boldsymbol{Alter_4}$	$<[0.3516, 0.4066], [0.0600, 0.0816], [0.0600, 0.0937]>$
Alternatives	$Crit_5$
	$<[T^L, T^U], [I^L, I^U], [F^L, F^U]>$
$\boldsymbol{Alter_1}$	$<[0.6365, 0.6608], [0.0013, 0.0045], [0.0045, 0.0081]>$
$\boldsymbol{Alter_2}$	$<[0.4958, 0.5208], [0.0291, 0.0375], [0.0333, 0.0375]>$
$\boldsymbol{Alter_3}$	$<[0.6427, 0.6635], [0.0006, 0.0022], [0.0022, 0.0046]>$
$\boldsymbol{Alter_4}$	$<[0.3516, 0.4066], [0.0600, 0.0816], [0.0600, 0.0937]>$

Table 12. The crisp decision matrix.

Alternatives	$\boldsymbol{Crit_1}$	$\boldsymbol{Crit_2}$	$\boldsymbol{Crit_3}$	$\boldsymbol{Crit_4}$	$\boldsymbol{Crit_5}$
$\boldsymbol{Alter_1}$	0.541771	0.81825	0.756698	0.81825	0.81825
$\boldsymbol{Alter_2}$	0.798031	0.798031	0.82659	0.733438	0.703125
$\boldsymbol{Alter_3}$	0.780531	0.823386	0.809927	0.823386	0.823386
$\boldsymbol{Alter_4}$	0.666667	0.733438	0.628125	0.580313	0.580313

Table 13. The normalized decision matrix.

Alternatives	$\boldsymbol{Crit_1}$	$\boldsymbol{Crit_2}$	$\boldsymbol{Crit_3}$	$\boldsymbol{Crit_4}$	$\boldsymbol{Crit_5}$
$\boldsymbol{Alter_1}$	1	0.896349	0.830087	0.709212	0.70921173
$\boldsymbol{Alter_2}$	0.678884	0.919059	0.759899	0.791223	0.82533333
$\boldsymbol{Alter_3}$	0.694105	0.890758	0.775533	0.704788	0.70478806
$\boldsymbol{Alter_4}$	0.812656	1	1	1	1

Table 14. s_i values.

Alternatives	$\boldsymbol{s_i}$
$\boldsymbol{Alter_1}$	0.17946
$\boldsymbol{Alter_2}$	0.210654
$\boldsymbol{Alter_3}$	0.252273
$\boldsymbol{Alter_4}$	0.040652

Table 15. ss_{ij} values.

Alternatives	$\boldsymbol{Crit_1}$	$\boldsymbol{Crit_2}$	$\boldsymbol{Crit_3}$	$\boldsymbol{Crit_4}$	$\boldsymbol{Crit_5}$
$\boldsymbol{Alter_1}$	0.17946	0.161	0.147838	0.120313	0.12031345
$\boldsymbol{Alter_2}$	0.145851	0.196885	0.165151	0.171976	0.17905884
$\boldsymbol{Alter_3}$	0.193855	0.234131	0.211966	0.196369	0.19636866
$\boldsymbol{Alter_4}$	0	0.040652	0.040652	0.040652	0.04065182

Table 16. w_j values.

Alternatives	$Crit_1$	$Crit_2$	$Crit_3$	$Crit_4$	$Crit_5$
E_1	0	0.018459	0.031621	0.059146	0.059146
E_2	0.064803	0.013769	0.045503	0.038677	0.031595
E_3	0.058417	0.018141	0.040307	0.055904	0.055904
E_4	0.040652	0	0	0	0
$\sum_k E_k$	0.163872	0.05037	0.117431	0.153728	0.146645
w_j	0.259272	0.079693	0.185795	0.243223	0.232017

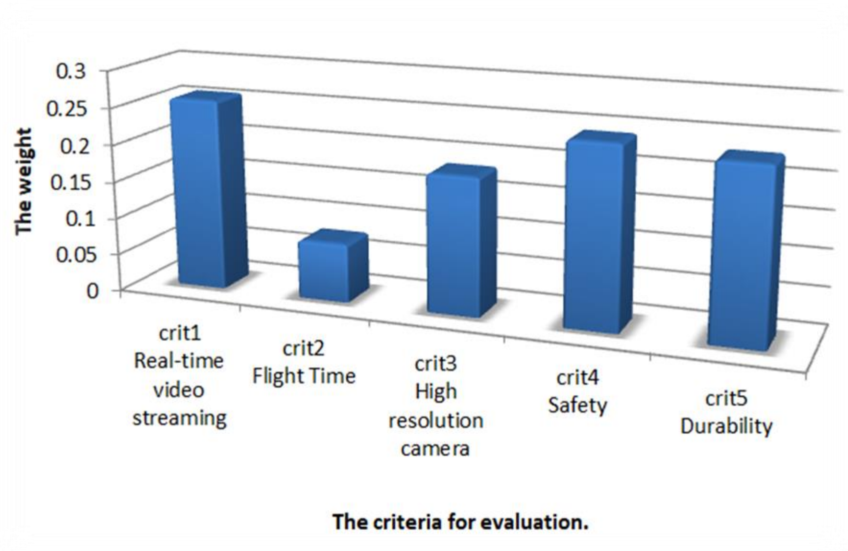

Figure 5. The criteria's ranking according to the final weight.

Step 3: Establish the alternatives ranking by adhering to the stages outlined in the IVN-EDAS approach. The initial steps of the IVN-EDAS approach involve creating the final decision matrix by sequentially executing steps 3.1.1 through 3.1.4, as outlined in Tables 5 to 12. Next, calculate the average solution (AVS) based on all criteria using Eqs. (10) and (11) presented in Table 17. Next, calculate the positive distance from average ($PDSA$) and negative distance from average ($NDSA$) matrices using Eqs. (12) and (13) sequentially and the criteria weights obtained before from the IVN-MEREC approach, as demonstrated in Tables 18 and 19.Then, calculate the weighted sum of $PDSA$ & $NDSA$ for all alternatives by applying Eqs. (14) and (15), as demonstrated in Table 20.After that, Normalize the values of $WS(PDSA)$ and $WS(NDSA)$ for all alternatives by utilizing Eqs. (16) and (17), as demonstrated in Table 21.

To conclude, calculate the assessment score (AS) for each alternative using Eq. (18), as the ranking of the alternatives is based on these scores, as demonstrated in Table 22. The alternative with the highest AS value is regarded as the optimal choice. Figure 6 illustrates the final ranking of the alternatives according to the IVN-EDAS method.

According to the proposed IVN-EDAS approach, the third alternative is the optimal choice for our case study, followed by the second alternative.

Table 17. AVS_j values.

AVS	$Crit_1$	$Crit_2$	$Crit_3$	$Crit_4$	$Crit_5$
$\mathbf{AVS_j}$	0.69675	0.79327615	0.755335063	0.73884646	0.731268333

Table 18. $PDSA_{ij}$ values.

Alternatives	$\boldsymbol{Crit_1}$	$\boldsymbol{Crit_2}$	$\boldsymbol{Crit_3}$	$\boldsymbol{Crit_4}$	$\boldsymbol{Crit_5}$
$\boldsymbol{Alter_1}$	0	0.03148192	0.001804304	0.10746961	0.118946306
$\boldsymbol{Alter_2}$	0.145362397	0.00599426	0.094335866	0	0
$\boldsymbol{Alter_3}$	0.120245784	0.03795612	0.072275237	0.11442076	0.125969491
$\boldsymbol{Alter_4}$	0	0	0	0	0

Table 19. $NDSA_{ij}$ values.

Alternatives	$\boldsymbol{Crit_1}$	$\boldsymbol{Crit_2}$	$\boldsymbol{Crit_3}$	$\boldsymbol{Crit_4}$	$\boldsymbol{Crit_5}$
$\boldsymbol{Alter_1}$	0.222431527	0	0	0	0
$\boldsymbol{Alter_2}$	0	0	0	0.00732082	0.038485645
$\boldsymbol{Alter_3}$	0	0	0	0	0
$\boldsymbol{Alter_4}$	0.043176654	0.0754323	0.168415408	0.21456956	0.206430152

Table 20. $WS(PDSA)_i$ & $WS(NDSA)_i$ values.

Alternatives	$\boldsymbol{WS(PDSA)_i}$	$\boldsymbol{WS(NDSA)_i}$
$\boldsymbol{Alter_1}$	0.056581	0.057670362
$\boldsymbol{Alter_2}$	0.055693	0.010709907
$\boldsymbol{Alter_3}$	0.104686	0
$\boldsymbol{Alter_4}$	0	0.148580157

Table 21. $Norm\ (PDSA)_i$& $Norm\ (NDSA)_i$ values.

Alternatives	$\boldsymbol{Norm\ (PDSA)_i}$	$\boldsymbol{Norm\ (NDSA)_i}$
$\boldsymbol{Alter_1}$	0.540478155	0.61185691
$\boldsymbol{Alter_2}$	0.532001247	0.92791832
$\boldsymbol{Alter_3}$	1	1
$\boldsymbol{Alter_4}$	0	0

Table 22. Alternative's assessment score (AS).

Alternatives	$\boldsymbol{AS_i}$	Rank
$\boldsymbol{Alter_1}$	0.57616753	3
$\boldsymbol{Alter_2}$	0.729959786	2
$\boldsymbol{Alter_3}$	1	1
$\boldsymbol{Alter_4}$	0	4

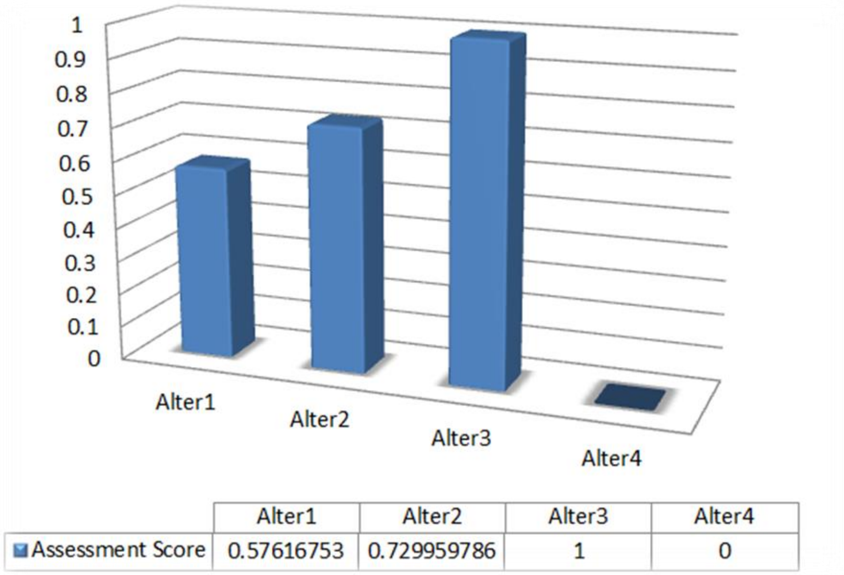

Figure 6. The alternative's ranking according to IVN-EDAS method.

5 | Sensitivity Analysis

A sensitivity analysis of the IVN-MEREC-EDAS data is necessary to evaluate the effectiveness and efficiency of the proposed approach. This analysis will demonstrate how different weights assigned to the criteria influence the final ranking of alternatives. Five cases are examined, as illustrated in Figure 7

Case 1: We set the weight of the first criterion, w_1, to 0.75 and the weights of the subsequent criteria, w_2: w_5, to the same value of 0.0625 in order to satisfy the condition $\sum_{i=1}^{n} w_j = 1$. Consequently, we discovered that the alternatives are presented in the subsequent order: $Alter_2 > Alter_3 > Alter_4 > Alter_1$

Case 2: The second criterion's weight, w_2, is assumed to be equal to 0.75, while the weights of the other criteria, w_1 and w_3: w_5, are assumed to be equal to 0.0625. We found that the alternatives are offered in the following sequence as a result: $Alter_3 > Alter_1 > Alter_2 > Alter_4$

Case 3: The weight of the third criterion, w_2, is assumed to be equal to 0.75, while the weights of the other two criteria, w_1: w_2 and w_4: w_5, are assumed to be equal to 0.0625. We found that the alternatives are offered in the following sequence as a result: $Alter_3 > Alter_2 > Alter_1 > Alter_4$

Case 4: The weight of the fourth criterion, w_4, is assumed to be equal to 0.75, while the weights of the other criteria w_1: w_3 and w_5, are assumed to be equal to 0.0625. We found that the alternatives are offered in the following sequence as a result: $Alter_3 > Alter_1 > Alter_2 > Alter_4$

Case 5: The weight of the fifth criterion, w_5, is assumed to be equal to 0.75, while the weights of the other criteria w_1: w_4, are assumed to be equal to 0.0625. We found that the alternatives are offered in the following sequence as a result: $Alter_3 > Alter_1 > Alter_2 > Alter_4$

The IVN-MEREC-EDAS approach presented in this work shows adequate stability for the criteria across various weight settings.

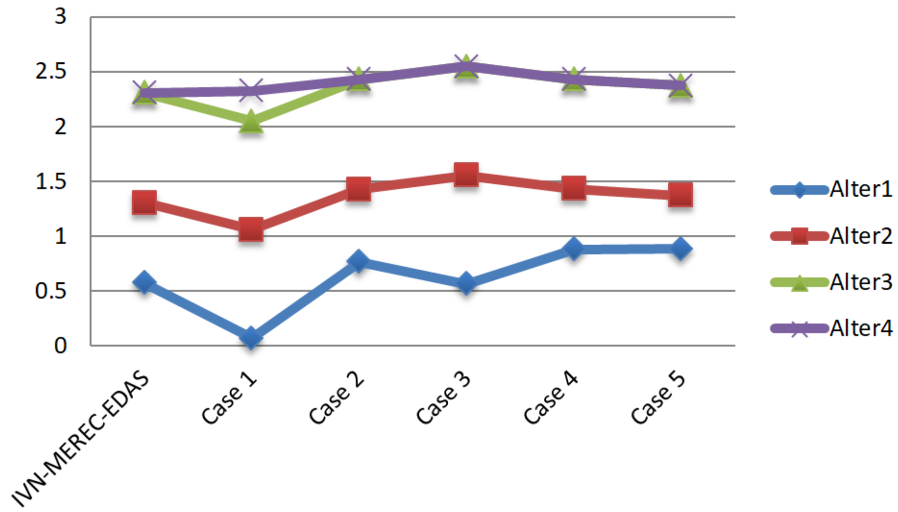

Figure 7. The impact of altering the weight on the outcomes.

6 | Comparative Analysis

The results of the IVN-MEREC method are compared with those of other recent and widely used MCDM methodologies for determining criterion weights. OWCM [23], WENSLO [24], CRITIC [25] and ENTROPY [26, 27]. The comparative outcomes of applying these MCDM approaches are shown in Figure 8. Table 23 shows Various Multi-Criteria Decision-Making (MCDM) methods are mentioned in the research.

We also compared the proposed IVN-EDAS approach with other MCDM methods for ranking alternatives to the same selection problem.: ARAS [28], RAM [29], MARICA [30].

We use Spearman's correlation, which is one of the best methods for determining whether two ordinal variables are associated.

$$SpCorrel = 1 - \left[\frac{6.\sum_{m=1}^{A}(differ)^2}{A.(A^2-1)}\right] \tag{19}$$

Where$A$, is the number of alternatives and $differ$ is the difference between the two ranks of the alternative. Table 24 displays the ranking of alternatives by comparing MCDM methods, demonstrating that our proposed IVN-EDAS method shows a strong correlation with both the ARAS, RAM, and MARICA methods. All the methods show that the third alternative is the best choice for the selected problem.

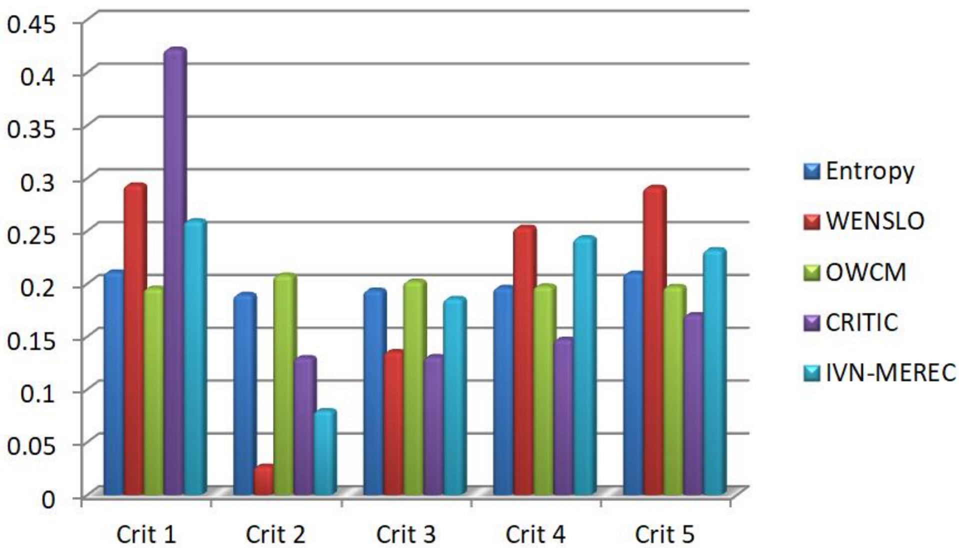

Figure 8. The criteria's weight according to various MCDM techniques.

Table 23. Various Multi-Criteria Decision-Making (MCDM) methods are mentioned in the research.

MCDM Method	Introduced by	Year
ARAS	Zavadskas and Turskis	2010
MARICA	Pamučar, D., L. Vasin, and L. Lukovac	2014
EDAS	Keshavarz Ghorabaee, Zavadskas, Olfat, and Turskis	2015
CRITIC	Diakoulaki, Mavrotas, and Papayannakis	1995
ENTROPY	Zeleny, M. and J. Cochrane	1982
WENSLO	Pamucar, D., et al.	2023
OWCM	Ahmed, A.D., M.M. Salih, and Y.R. Muhsen	2024

Table 24. The alternatives ranking by comparing MCDM approaches.

Alternatives	RAM (RI_i)	Rank	MARICA (Q_i)	Rank	ARAS (K_i)	Rank	IVN-EDAS (AS_i)	Rank
$Alter_1$	1.499909	3	0.084824	3	0.896005	3	0.576168	3
$Alter_2$	1.503744	2	0.057336	2	0.936921	2	0.72996	2
$Alter_3$	1.508699	1	0.002695	1	0.990444	1	1	1
$Alter_4$	1.487567	4	0.162133	4	0.763405	4	0	4

7 | Managerial Implications

Integrating Unmanned Aerial Vehicles (UAVs) into smart city initiatives is a complex area of study. It encompasses several aspects, including the integration of Mobile- Edge Computing (MEC) with UAVs, the application of artificial intelligence in surveillance, the architecture needed for interactions between smart cities and UAVs, security considerations related to the Internet of Drones (IoD), cyber security challenges faced by smart cities, and ethical concerns surrounding the use of drones. Researchers and policymakers are particularly focused on security and privacy issues within smart cities. Smart cities aim for sustainability by enhancing employment opportunities, boosting commerce, and fostering community development. These aspects drive economic growth, attract investments, and improve urban planning and management. Also, this study is valuable because it will assist stakeholders such as legislators, urban planners, and experts in smart city management to enhance the resilience and safety of smart cities.

8 | Conclusion

We proposed an integrated approach that combines two Multi-Criteria Decision-Making (MCDM) methods: the MEREC method for calculating the weights of criteria and the EDAS method for ranking alternatives, the EDAS is highly useful when there are opposing characteristics, and the optimum option is selected by figuring out how far each alternative deviates from the ideal value. Our proposed approach operates within a neutrosophic framework, which addresses issues of uncertainty and lack of information that often arise in decision-making processes. Experts' evaluations were based on an interval-valued neutrosophic number scale, which represents the degree of confidence in their assessments. This approach assists in evaluating and selecting the best MEC-integrated UAV from various proposed alternatives to enhance safety and protection in smart cities.

The results of our experimental study have demonstrated the model's effectiveness. Among all the criteria, the real-time video criterion is the most preferred, and the third alternative (DJI Mavic 3T) ranks highest.

Our approach was applied to only four alternatives and five criteria. In future work, we will apply our approach to a larger number of criteria and alternatives to explore its applicability with big data.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors

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