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DRONE SELECTION FOR FOREST SURVEILLANCE AND FIRE DETECTION USING INTERVAL VALUED NEUTROSOPHIC EDAS METHOD

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Abstract. *Forest fires are one of the major causes for deforestation resulting in significant economic and environmental losses. The application of drones has been extended to various areas including disaster management. Since drones offer numerous advantages like real-time surveillance, task planning capabilities and autonomy, they are utilized in early detection systems for forest fires. The selection of a drone type for this purpose involves a complex system of multiple factors and conflicting information, for which the use of multi-criteria decision-making (MCDM) methods have been found to be yielding effective results. The aim of this study is to present a decision framework for drone selection problem in the context of forest fire surveillance and detection. This study contributes by (i) pointing out to the gap that the drone selection problem for forest surveillance and fire detection has been sparsely addressed, (ii) presenting an extensive literature review, (iii) extracting the relevant criteria through a literature review and interviews with the experts in field, (iv) assessing the alternatives by the proposed framework based on interval valued neutrosophic evaluation based on distance from average solution (IVN EDAS) method. The proposed framework is demonstrated by a case study consisting of four drone alternatives and 14 criteria. In accordance with the extant literature, the criteria related to the visual capabilities and diagnosis are evaluated as the most crucial features. A sensitivity analysis is carried out to check for the robustness by varying the criteria weights and a comparative analysis is conducted with interval valued neutrosophic technique for preference by similarity to the ideal solution (IVN TOPSIS) and interval valued neutrosophic combinative distance-based assessment (IVN CODAS) methods to validate the veracity of the method.*

Key words: *Drone Selection, Forest Surveillance, Fire Detection, Interval Valued Neutrosophic Sets, MCDM, EDAS*

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1. INTRODUCTION

Forests are vital for the sustainability of the ecosystem and human life. They play a crucial role in counteracting climate change and its worsening effects. Among the deforestation causes, wildfires have been responsible for about 34% of the tree cover loss since 2019 [1]. Increasing wildfires and deforestation exacerbate the effects of climate change which lead to a vicious cycle of drier seasons followed by more frequent and intense fires. One of the most devastating wildfires in history occurred in the 2019-2020 Australian bushfire season, the burnt area had been estimated to be between 24.3 and 33.8 million hectares [2], which was effective from June 2019 to May 2020. In total, 33 people have lost lives, 3.094 houses have been destroyed and the direct economic cost has been estimated to be $2.5 billion in addition to $4-5 billion worth of losses on the Australian food and agriculture industry [3]. Deforestation substantially damages the economy and the ecosystem, which is avoidable to some extent. One of the ways to reduce these damages is to take environmental precautions and extinguish the fire as soon as they occur. As time passes, the destructive effect of wildfires magnifies abruptly. A rule has been mentioned i.e., the amount of water that is required to suppress a fire burning for a minute is multiplied by ten when the burning time doubles [4]. Thus, early detection and taking countermeasures on time are crucial to prevent significant damage.

For this reason, various technologies have found its application for monitoring and detection of forest fire. The technologies used can be summarized as satellite-based, sensor-based, camera-based, mobile biological sensing, unmanned aerial vehicle (UAV), radio-acoustic based, neural network based and fuzzy logic based technologies according to the recent classification done by Chowdary et al. [5]. In practice, many of these technologies cannot be deployed as effective stand-alone systems, instead a combination of these technologies is utilized to enhance the accuracy and efficiency in detection. However, each of these technologies are associated with certain advantages and disadvantages. In comparison to the satellite-based and ground-based technologies with static topology, the use of drones brings several useful properties such greater maneuverability and real-time surveillance, especially in the areas that are difficult to access. Further, drones provide autonomy, task planning capabilities and self-healing properties [6]. The radical growth in the sensor and micro-processing technologies have facilitated their usage in different areas including the fire detection systems. The sensor technologies serve with improved preciseness and fewer false alarms notably when utilizing different types of sensors. Thus, the application of drones integrated with different technologies as sensors and neural networks can realize an effective and self-sufficient solution for the surveillance and detection of forest fires. The application of drones and its potential for the respective problem requires more attention for the future research.

There are several factors affecting the performance of the deployed drone type in the respective context. Thus, the problem of its selection contains several ambiguities, that arise from several sources such as multiple evaluation attributes, the uncertainty and bias incorporated into the human decision-making process as well as the factors and the characteristics affecting the performance of a drone. According to Hristozov and Zlateva [7], the performance of a drone is influenced by its internal attributes, which are the technical features, and the external attributes such as the characteristics of the area, weather and other environmental conditions. Some of these attributes may be in trade-off or have interrelationships with one and other. Such complex decision-making problems that involve inexplicable and unquantifiable relationships are broadly handled by the multi-criteria decision-making (MCDM) methods, since they yield appropriate results with significantly lower computation time and complexity.

The vagueness and uncertainty present in information can be successfully represented by fuzzy logic introduced by Zadeh [8]. Turksen [9] extended fuzzy sets to interval valued fuzzy sets to enable for a range of values to be assigned in the membership information. Smarandache [10] introduced the neutrosophic sets, which enable the representation of hesitancy in addition to the membership and non-membership information, as an extension to intuitionistic fuzzy sets [11]. Moreover, fuzzy MCDM methods are particularly helpful in addressing the decision-making problems with uncertainty and ambiguity resulting from the subjective evaluations and vague relationships among criteria and alternatives. Among many proposed MCDM methods, evaluation based on distance from average solution (EDAS) method by Keshavarz Ghorabaee et al. [12] processes the conflicting criteria and performs better at considering the intangibility and vagueness in the decision-making process [13]. It also handles with the biased information better since its calculation is based on the assessment by the average solution. For this reason, this study aims to handle the drone selection problem for monitoring and detection of forest fires by proposing a framework using interval valued neutrosophic (IVN) sets to present the vague and uncertain linguistic information and EDAS method to evaluate the alternatives based on the conflicting criteria. The findings from the case study demonstrate that "the camera accuracy" is the most significant feature for a drone used in forest surveillance and fire detection. The "ingress protection rating", "maximum flight time" are the second and third most significant characteristics. The rest of the criteria are ranked with the following order: "wind resistance", "camera resolution", "zoom camera", "maximum operation altitude", "maximum horizontal speed", "maximum hover time", "operation frequency", "obstacle sensors", "maximum takeoff weight", "charging time" and "hovering accuracy".

This study contributes to literature by pointing out to the gap that the drone selection problem for forest surveillance and fire detection has been sparsely addressed, by presenting an extensive literature review on the technologies deployed in forest monitoring and fire detection, and by extracting the relevant criteria through an extensive literature review and interviews with the experts in field. As a result, four drone alternatives and 14 criteria have been identified. The alternatives are then evaluated based on the proposed framework using IVN EDAS method. Moreover, a sensitivity analysis is conducted in order to check for the robustness of the results by varying the criteria weights. The veracity of the results is validated by carrying out a comparative analysis with interval valued neutrosophic technique for preference by similarity to the ideal solution (IVN TOPSIS) method and interval valued neutrosophic combinative distance-based assessment (IVN CODAS) method.

The rest of this paper is structured as follows. Section 2 presents an in-depth literature review on the other technologies and the application of drones in the respective context along with the examination of drone selection problem by the MCDM methods. Section 3 provides the methodology of IVN EDAS method with the preliminaries of interval valued neutrosophic sets. Then, Section 4 presents the application of the method on a case study that is concluded with a sensitivity analysis and a comparative analysis with IVN TOPSIS and IVN CODAS methods. Lastly, Section 5 gives the conclusion with the recommendations for future study.

2. Literature Review

Monitoring and early detection of a possible fire are as crucial as the fast response and suppression of wildfires to avoid irreversible damages. Several studies have examined the technologies used in forest fires and investigated their benefits and drawbacks. We first summarize these technologies and then discuss the advantages of the application of drones in forest surveillance and fire detection. Den Breejen et al. [14] categorized the techniques used in forest fire monitoring and detection into three groups as ground-based systems, manned aerial vehicle-based systems, and satellite-based systems. In their classification, a ground-based system monitors and gathers information by utilizing equipment with static topology. Manned aerial vehicle-based systems describe systems that use an aerial vehicle controlled by a human operator to patrol the area for the detection of a possible fire. In satellite-based systems, the imagery taken through the satellite is collected and processed with the image-processing techniques. Recent technological advancements in the field of wireless networks, microprocessors, image-processing and artificial intelligence have enabled a variety and a combination of these methods for the monitoring and detection purposes of forest fires. Alkhatib [4] generalized the detection and monitoring systems as suppression and detection techniques used by the authorities, satellite-based systems, optical sensors, and digital camera and wireless sensor networks (WSN). The suppression and detection techniques used by the authorities include watch towers, water tankers, lightning detectors, etc. Among the optical sensor and digital camera technologies, the video-cameras sensitive to smoke, infrared thermal imaging cameras and light detection and ranging systems (LIDAR) are widely applied. In WSNs, the area of interest is surveilled by multiple wireless nodes that are equipped with different types of sensors and microprocessors. Depending on the movement capability of nodes, WSNs are classified as WSN with static topology and WSN with dynamic topology. In WSNs with dynamic topology, the nodes follow a common protocol. Chowdary et al. [5] extended this classification by sensor-based, neural networks-based, drone/airborne-based, fuzzy logic, mobile biological sensing-based, and radio acoustic-based techniques. By fuzzy logic techniques, a fuzzy logic algorithm is created and applied to the visual data gathered from various sources. The proposed fuzzy logic algorithm may use instances such as temperature, smoke, light, humidity, and distance [15] and shape, size, and motion variation of the fire [16] for which membership functions are generated. Then for the verification, the performance of the decision-making procedure is evaluated either by simulations or real fire datasets. In mobile biological sensing-based detection, certain animal groups may be equipped with sensor and global positioning system (GPS) devices transmitting data and location information, which are examined for sudden environmental changes such as temperature or humidity or changes in animal behavior. In practice, many systems combine multiple techniques together for more precision in monitoring and detection. Many forest fire surveillance systems aim to deploy a self-sufficient system that require little or no maintenance or supervision. Ideally, the deployed system should monitor the forest and detect the fire as soon as possible with a low false alarm chance. Also, it should inform the authorities automatically. From the studies that have dealt with these technologies' advantages and disadvantages, it has been found that the satellite-based techniques have a low temporal and spatial resolution [17]. The quality of imagery is highly affected by the terrain, time of day, and weather [5] resulting in limited coverage, limited precision, and a lack of real-time data reporting [6]. Radio acoustic-based methods are prone to fire localization errors and a high chance of false alarms [5]. In camera-based technologies, immobile cameras equipped with multiple types of sensors are positioned at specified locations for surveillance. Immobile cameras provide a limited surveillance range [18] and image and video processing techniques are associated with significant pre-processing time and effort [5]. Generally used miniaturized infrared cameras have low sensitivity, which leads to a high false alarm possibility [5, 19]. Neural network-based techniques require large datasets and heavy model sizes, which are also prone to various false alarms [5]. Sensor-based techniques provide more accuracy in the surveillance and detection of forest fires than satellite-based techniques as these are deployable in areas that are not observable by satellites [20]. However, WSNs with static topology require regular maintenance of the infrastructure and they have limited coverage and effectiveness [21]. As these systems operate as static infrastructure, they are prone to get destroyed in the event of a fire which may cause additional replacement costs. Their effectiveness in terms of coverage and resolution is directly determined by the investment made into the deployed system [6].

Satellite-based and ground-based techniques such as camera surveillance and WSNs with static topology may be insufficient for precise real-time monitoring of large areas. Drones offer greater maneuverability and real-time surveillance capabilities in areas hard to access. Recent progressive improvements in micro-processing, imaging, and drone technologies facilitate lower costs and wider usage of these technologies. The type of sensors utilized in the surveillance drones can be chosen depending on the type of possible fire and topology of the area to increase precision in detection. In the equipment with different types of sensors, a similarity index of measurements helps to mitigate the chance of false alarms [22]. In addition, the major conveniences of drones are that they provide great autonomy and task-planning capabilities with efficient allocation, self-organization, and self-healing properties [6].

For the sustainability and security of the system, the selection of the drone model is as important as the system architecture, sensors, and its other fundamental components. Among a great variety of drones available on the market, a drone needs to be selected that is most appropriate to the characteristics of the area and can satisfy the necessary requirements for the tasks.

Many factors impact the operational performance of a drone and thus its selection, these factors can be viewed as external factors and internal characteristics or attributes of a drone [7]. The external factors are the disaster type, the characteristics of the area of interest, and the weather and other environmental conditions. For instance, it has been found that strong wind and precipitation affect drones' performance significantly [23, 24]. Under the influence of the strong wind, the movement capability of a drone is significantly disrupted which may result in the deviation from its direction and poor stabilization during hovering. The stabilization of a drone is especially important for the quality of imaging. Other environmental conditions such as temperature and altitude of the area must be considered since drones are not able to operate at all conditions.

With the wide-ranging features and integrable nature of drones, they have a substantial role as a dynamic, deployable, and controllable component of the Internet of Things infrastructure [25, 26]. Drones have been manufactured and used primarily for military and security purposes. Their application areas are extended to natural disasters, agricultural fields and smart farming, cargo handling, delivery of medical goods, traffic management, conservation, and land monitoring, climate change and urban planning, and more. Therefore, they are available with various features and attributes such as drone type, weight, speed, takeoff weight, hover time, charging time, flight time, operating altitude, etc. [27, 28]. Yet some of these attributes are in trade-off with one another. As an example, drones with higher speed capability have lower payload capacity [29, 30], and typically drones with slower speed can take shorter distances and handle higher payloads [31]. As a result, the drone selection problem must consider these multiple external factors and conflicting internal attributes, which makes it a highly complex and a challenging task.

This study focuses on the drone selection problem for monitoring and detection of forest fires. The application of drones in the wildfire context is studied by many authors. To our best knowledge, the studies on the drone usage in wildfires are mainly gathered on three scopes: vision-based techniques and (deep learning) image-processing techniques [19, 32, 33], the system architecture with communication, data receiving, and GIS modules [34, 35], and the area coverage and coordination of multiple drones [5, 36, 37, 38]. Yuan et al. [19] presented the first thorough analysis of technologies that use drones for fire detection, diagnosis, prognosis, image vibration elimination, and cooperative control of drones. Bailon-Ruiz and Lacroix [39] reviewed a selection of studies that examine drone application in wildfire remote sensing based on an autonomy perspective using three metrics: situation awareness, decisional ability, and collaboration ability. Akhloufi et al. [6] presented an extensive review with a focus on onboard sensor instruments, fire perception algorithms, and coordination strategies. The prior studies reviewed by [6, 19, 39] assumed that a set of drones are available and suited for their specific use and thus the drone selection problem has not been mentioned. Regarding the drone selection problem, Hristozov and Zlateva [7] introduced a performance mapping model as a concept model for drone selection in specific disaster conditions to aid the drone selection decision process. To best of our knowledge, in the literature only the study by Pamučar et al. [40] dealt with the drone selection problem related to forest fire uses. Their study focused on determining a drone model that can be used as a physical fire suppression tool that is controlled by operators in a ground central system. Our study distinguishes from the prior study in that it deals with the drone selection problem for the monitoring and detection of forest fires for its application as an early warning system that requires minimum human assistance. Using a drone for monitoring and detection purposes and as a fire suppression tool require different technical characteristics. A network of drones can act as mobile wireless sensor network, where the drones are equipped with various sensors to collect data on temperature, smoke and other parameters. The collected data should be transmitted to a head cluster thereafter it is transmitted to gateway to get processed. The drones in a WSN require to follow a protocol for self-organized deployment and coverage of the area. The energy efficiency in WSN communication is of major concern for an effective communication [41, 42]. Likewise, each drone has a limited payload. The higher the payload of a drone, the higher is its battery consumption and shorter is its flight time. Therefore, the weight of a drone should be ideally kept low [43]. Thus, the energy consumption of a drone and of the WSN communication are two fundamental issues concerning the effectiveness of the whole as a fire detection system, one contributing to the movement capability and other to the efficient data transmission. To utilize a drone additionally as a firefighting tool, it should be equipped with fire extinguishing instruments. As a result, it would increase its payload and shorten the endurance of a drone. Therefore, we believe that the drone selection for monitoring and detection and for firefighting purpose should be examined separately. Ideally, both drone networks shall be integrated to each other as first one would act as an early warning system signaling the latter one to counteract the starting fire timely.

To address the drone selection problem, neutrosophic sets are preferred to represent the ambiguity present in the linguistic assessments of the decision makers (DMs). Different types of uncertainties are associated in the decision-making processes, which can be considered with the help of fuzzy logic introduced by Zadeh [8]. Fuzzy sets have been extended to intuitionistic fuzzy sets by Atanassov [11] which describe both the membership and the non-membership degree. To enable the representation of indeterminacy in information of which the intuitionistic fuzzy sets lack, neutrosophic sets have been developed by Smarandache [10]. Following that, different extensions of neutrosophic sets have been introduced such as interval-valued neutrosophic sets, type-2 neutrosophic sets, 2-tuple linguistic neutrosophic sets. Numerous studies have applied EDAS method in neutrosophic environment of these extensions such as single-valued neutrosophic sets [44], interval valued neutrosophic sets [45], type-2 neutrosophic sets [46] and bipolar neutrosophic sets [47].

The MCDM methods have found a great variety of application areas thanks to their beneficial aspects. In the presence of complex systems which incorporate multiple criteria and when the interrelationships among the systems' elements are vague and inexplicable by the mathematical models, MCDM methods provide a structured (group) decision making process that is easy to implement, handles the uncertainty, can deal with both quantitative and qualitative data, and provides fast and relatively reliable solutions. It is basically used to select or prioritize alternatives based by assessing on a set of criteria or attributes. MCDM methods are used in various types of decision making problems such as the selection of suppliers [48], the evaluation of potential locations for specific uses [49, 50], but also is applied for the strategy selection [51, 52], performance evaluation [53, 54], and risk evaluation [55] among many others. The EDAS method is utilized by various recent studies with different extensions and application areas. Simic et al. [46] used a type-2 neutrosophic number based threshold-based attribute ratio analysis (ITARA) method integrated with EDAS model for route selection of petroleum transportation. Menekse et al. [56] applied a Pythagorean fuzzy criteria importance through intercriteria correlation (CRITIC) method integrated with EDAS model for the selection of an additive manufacturing process for automotive industry. Dhumras and Bajaj [57] used a picture fuzzy soft Dombi EDAS model for strategy selection for sustainable and smart (robotic) agrifarming.

There are several studies that dealt with the drone selection problem using MCDM methods in other application areas of drones. To give a few examples from the recent studies, for the military purposes a fuzzy weighted average algorithm is applied for group decision-making by Lin and Hung [58]. Hamurcu and Eren [59] proposed a methodology based on analytical hierarchy process (AHP) and technique for preference by similarity to the ideal solution (TOPSIS), and a fuzzy analytical hierarchy process-vise kriterijumska optimizacija i kompromisno resenje (AHP-VIKOR) hybrid model is proposed by Radovanović et al. [60]. The AHP-TOPSIS method is used by several studies for the civilian application areas [61, 62]. With the radical growth in the E-commerce, delivery by drones has gained significant attention as a delivery tool since delivery in conventional ways has become rather inconvenient due to high delivery times and increasing costs in transportation. In this context, Nur et al. [28] performed an interval valued inferential fuzzy (IVIF) TOPSIS method to find the most suitable drone for package delivery purposes in urban and rural areas and Banik et al. [63] proposed a graph theory and matrix approach to select a drone for the delivery of medical supplies. The examination of the literature shows that the drone selection for the usage against forest fires has been addressed only by Pamučar et al. [40] in terms of selecting a drone with the capability of extinguishment. No prior study has focused on the drone selection solely for the purpose of forest surveillance and fire detection. The next section presents the proposed methodology.

3. METHODOLOGY

The EDAS method, introduced by Keshavarz Ghorabaee et al. [12], is a distance-based method similar to TOPSIS method and VIKOR method. Instead of using positive ideal and negative ideal solutions, EDAS method evaluates the alternatives by using the positive and negative distance to the average solution. This aspect reduces the impact of DMs' bias. It recognizes the conflicting criteria [12, 64] and represents the ambiguity in the decision-making process [13]. The presence of the conflicting criteria makes EDAS method more suitable for this problem. However, the MCDM methods are prone to the rank reversal phenomenon [65] and the results should be further checked against this issue. It occurs when the introduction or the exclusion of a non-optimal alternative modifies the optimal and/or the least preferred alternative. It has been found that the EDAS method performs better than TOPSIS in terms of robustness to the rank reversal phenomenon [66].

The interval valued neutrosophic sets are used to represent the linguistic evaluations of the DMs since this set allows for an enriched representation of information since only the lower values of the parameters (membership, hesitancy, and non-membership) must be equal to or lower than 3, and the sum of upper values can exceed 3 allowing for a flexible information representation. Therefore, the EDAS method under the interval valued neutrosophic environment is selected as an appropriate method to consider the ambiguity in decision making and conflicting criteria. In this section, we introduce the IVN EDAS method and provide the details about its implementation.

3.1 Preliminaries for Interval Valued Neutrosophic Sets

Definition 1: Let X be the universe. For each element x in X, an IVN set is be defined by three parameters; the truth-membership $T_N(x)$, indeterminacy (hesitancy)-membership $I_N(x)$, and the falsity-membership $F_N(x)$, where $T_N = \left[T^{\,L}_{N(x)}, T^{\,U}_{N(x)} \subseteq [0,1]\right], I_N(x) = \left[I^{\,L}_{N(x)}, I^{\,U}_{N(x)} \subseteq [0,1]\right]$, and $F_N(x) = \left[F^{\,L}_{N(x)}, F^{\,U}_{N(x)} \subseteq [0,1]\right]$.

An interval valued neutrosophic number (IVNN) satisfies the following condition that the sum of the lower values of these three elements must be lower than or equal to 3: $0 \leq T^{\,L}_{N(x)} + I^{\,L}_{N(X)} + F^{\,L}_{N(x)} \leq 3$. Thus, an IVN set is defined as in Eq. (1) [67]:

$$\mathrm{N} = \left\{\langle \mathrm{x}, \left[\mathrm{T}^{\,\mathrm{L}}_{\mathrm{N(x)}}, \mathrm{T}^{\,\mathrm{U}}_{\mathrm{N(x)}}\right], \left[\mathrm{I}^{\,\mathrm{L}}_{\mathrm{N(x)}}, \mathrm{I}^{\,\mathrm{U}}_{\mathrm{N(x)}}\right], \left[\mathrm{F}^{\,\mathrm{L}}_{\mathrm{N(x)}}, \mathrm{F}^{\,\mathrm{U}}_{\mathrm{N(x)}}\right]\rangle \mid \mathrm{x} \in \mathrm{X}\right\}. \tag{1}$$

Let a and b be two IVNNs represented by $[T^{\,L}_{a}, T^{\,U}_{a}], [I^{\,L}_{a}, I^{\,U}_{a}], [F^{\,L}_{a}, F^{\,U}_{a}]$ and $[T^{\,L}_{b}, T^{\,U}_{b}], [I^{\,L}_{b}, I^{\,U}_{b}], [F^{\,L}_{b}, F^{\,U}_{b}]$, respectively. Following mathematical operations are applied between two IVNNs a and b as defined below [68]:

$$a^c = \langle [T^{\,L}_{a}, T^{\,U}_{a}], [1 - I^{\,L}_{a}, 1 - I^{\,U}_{a}], [F^{\,L}_{a}, F^{\,U}_{a}] \rangle, \tag{2}$$

$a \subseteq b$ if and only if $a \subseteq b$ and only if

$$T^{\,L}_{a} \leq T^{\,L}_{b}, T^{\,U}_{a} \leq T^{\,U}_{b}; I^{\,L}_{a} \geq I^{\,L}_{b}, I^{\,U}_{a} \geq I^{\,U}_{b}; \ F^{\,L}_{a} \geq F^{\,L}_{b}, F^{\,U}_{a} \geq F^{\,U}_{b}, \tag{3}$$

$$a = b \text{ if and only if } a \subseteq b \text{ and } b \subseteq a \tag{4}$$

$$a \oplus b = \langle \begin{matrix} \left[T_a^L + T_b^L - T_a^L T_b^L, T_a^U + T_b^U - T_a^U T_b^U\right], \\ \left[I_a^L I_b^L, I_a^U I_b^U\right], \left[F_a^L F_b^L, F_a^U F_b^U\right] \end{matrix} \rangle, \tag{5}$$

$$a \otimes b = \langle \begin{matrix} \left[T_a^L T_b^L, T_a^U T_b^U\right], \left[I_a^L + I_b^L - I_a^L I_b^L, I_a^U + I_b^U - I_a^U I_b^U\right], \\ \left[F_a^L + F_b^L - F_a^L F_b^L, F_a^U + F_b^U - F_a^U F_b^U\right] \end{matrix} \rangle. \tag{6}$$

Definition 2: A set of IVNNs is represented by the notation $x_k = \langle [\mathrm{T}_k^L, \mathrm{T}_k^U], [\mathrm{I}_k^L, \mathrm{I}_k^U], [\mathrm{F}_k^L, \mathrm{F}_k^U] \rangle$, where k is the expert $(k = 1,2,3, \dots, K)$. To aggregate multiple IVNNs, the interval valued neutrosophic weighted arithmetic operator (INNWA) is defined as follows [68]:

$$INNWA(x_1, x_2, \dots, x_K) = \sum_{k=1}^{K} y_k x_k = \left[1 - \prod_{k=1}^{K}\left(1 - T_k^L\right)^{y_k}, 1 - \prod_{k=1}^{K}\left(1 - T_k^U\right)^{y_k}\right],$$
$$\langle \left[\prod_{k=1}^{K}\left(I_k^L\right)^{y_k}, \prod_{k=1}^{K}\left(I_k^U\right)^{y_k}\right], \left[\prod_{k=1}^{K}\left(F_k^L\right)^{y_k}, \prod_{k=1}^{K}\left(F_k^U\right)^{y_k}\right] \rangle, \tag{7}$$

where y_k denotes the weight vector of the experts.

Definition 3: The deneutrosophication function of an IVNN a is calculated using Eq. (8) [69]:

$$K(a) = \left(\left(\frac{(T_a^L + T_a^U)}{2}\right) + \left(1 - \frac{(I_a^L + I_a^U)}{2}\right)\left(I_a^U\right) - \left(\frac{(F_a^L + F_a^U)}{2}\right)\left(1 - F_a^U\right) \right), \tag{8}$$

where $a = \langle [T_a^L, T_a^U], [I_a^L, I_a^U], [F_a^L, F_a^U] \rangle$.

Definition 4: Let a and b be two IVNNs represented by $[T_a^L, T_a^U], [I_a^L, I_a^U], [F_a^L, F_a^U]$ and $[T_b^L, T_b^U], [I_b^L, I_b^U], [F_b^L, F_b^U]$, respectively. The Euclidean distance between two IVNNs are given by Eq. (9) [70]:

$$d_E(a, b) = \sqrt{\frac{1}{6}\left(\left(\begin{matrix} (T_a^L - T_b^L)^2 + (T_a^U - T_b^U)^2 + (I_a^L - I_b^L)^2 + \\ (I_a^U - I_b^U)^2 + (F_a^L - F_b^L)^2 + (F_a^U - F_b^U)^2 \end{matrix}\right)\right)}. \tag{9}$$

Definition 5: The function in Eq. (10) returns the Euclidean distance if the difference between two deneutrosophicated IVNNs is greater than zero, otherwise it returns zero.

$$Z(a, b) = \begin{cases} d_E(a, b), & \text{if } K(a) - K(b) > 0, \\ 0, & \text{if } K(a) - K(b) \le 0, \end{cases} \tag{10}$$

where $a = [T_a^L, T_a^U], [I_a^L, I_a^U], [F_a^L, F_a^U]$, $b = [T_b^L, T_b^U], [I_b^L, I_b^U], [F_b^L, F_b^U]$.

3.2 Interval Valued Neutrosophic EDAS Method

This section presents the steps of the proposed IVN EDAS method. The proposed method addresses a group decision making problem that is under the assumption that there are the set of n alternatives $X = \{X_1, X_2, \dots, X_i, \dots, X_n\}$ evaluated based on m criteria $C = \{C_1, C_2, \dots, C_j, \dots, C_m\}$ by K DMs $D = \{D_1, D_2, \dots, D_k, \dots, D_K\}$. In the rest of this section, the steps of the proposed IVN EDAS method are presented.

Step 1: The linguistic evaluations of each expert are collected regarding the alternatives' performance with respect to the criteria. These linguistic evaluations are converted to IVNNs by using the IVN scale given in Table 1 to obtain the IVN matrix of each expert as presented in Table 2, where $x_{ijk} = \langle [T^{L}_{ijk}, T^{U}_{ijk}], [I^{L}_{ijk}, I^{U}_{ijk}] [F^{L}_{ijk}, F^{U}_{ijk}] \rangle$ is an IVN evaluation of the expert k on the performance of alternative i with respect to criterion j. Based on the knowledge and competency, the experts are assessed and assigned an importance weight y_k.

Table 1 IVN Scale for alternative evaluation [45]

Linguistic Terms		$\langle \boldsymbol{T}, \boldsymbol{I}, \boldsymbol{F} \rangle$
CL	Certainly Low	⟨[0.05, 0.2], [0.6, 0.7], [0.75, 0.9]⟩
VL	Very Low	⟨[0.15, 0.3], [0.5, 0.6], [0.65, 0.8]⟩
L	Low	⟨[0.25, 0.4], [0.4, 0.5], [0.55, 0.7]⟩
BA	Below Average	⟨[0.35, 0.5], [0.3, 0.4], [0.45, 0.6]⟩
A	Average	⟨[0.40, 0.6], [0.1, 0.2], [0.40, 0.6]⟩
AA	Above Average	⟨[0.45, 0.6], [0.3, 0.4], [0.35, 0.5]⟩
H	High	⟨[0.55, 0.7], [0.4, 0.5], [0.25, 0.4]⟩
VH	Very High	⟨[0.65, 0.8], [0.5, 0.6], [0.15, 0.3]⟩
CH	Certainly High	⟨[0.75, 0.9], [0.6, 0.7], [0.05, 0.2]⟩

Table 2 IVN decision matrix of an expert k

Crit.	***AL*₁**	***ALₙ***
C_1	$[T^L_{11k}, T^U_{11k}], [I^L_{11k}, I^U_{11k}], [F^L_{11k}, F^U_{11k}]$	$[T^L_{n1k}, T^U_{n1k}], [I^L_{n1k}, I^U_{n1k}], [F^L_{n1k}, F^U_{n1k}]$
$\vdots$	$\vdots$	$\vdots$
C_m	$[T^L_{1mk}, T^U_{1mk}], [I^L_{1mk}, I^U_{1mk}], [F^L_{1mk}, F^U_{1mk}]$	$[T^L_{nmk}, T^U_{nmk}], [I^L_{nmk}, I^U_{nmk}], [F^L_{nmk}, F^U_{nmk}]$

Step 2: To obtain the aggregated IVN decision matrix, the IVN decision matrix of the experts are aggregated by using the INNWA operator defined in Eq. (7). Table 3 shows the representation of the aggregated IVN decision matrix x_A, where $x_A = [x_{ijA}]_{n*m} = \langle [T^{L}_{ijA}, T^{U}_{ijA}], [I^{L}_{ijA}, I^{U}_{ijA}] [F^{L}_{ijA}, F^{U}_{ijA}] \rangle$ represents the aggregated evaluation of the experts for the alternative i with respect to criterion j.

Step 3: Each expert k evaluates the criteria importance with linguistic terms. These evaluations are converted to IVNNs using the scale given in Table 4. The following criteria weights matrix is obtained for each expert k:

$$W = [w_{jk}]_{1*m} \tag{11}$$

Table 3 Aggregated IVN decision matrix

Crit.	***AL*₁**	***ALₙ***
C_1	$[T^L_{11A}, T^U_{11A}], [I^L_{11A}, I^U_{11A}], [F^L_{11A}, F^U_{11A}]$	$[T^L_{n1A}, T^U_{n1A}], [I^L_{n1A}, I^U_{n1A}], [F^L_{n1A}, F^U_{n1A}]$
$\vdots$	$\vdots$	$\vdots$
C_m	$[T^L_{1mA}, T^U_{1mA}], [I^L_{1mA}, I^U_{1mA}], [F^L_{1mA}, F^U_{1mA}]$	$[T^L_{nmA}, T^U_{nmA}], [I^L_{nmA}, I^U_{nmA}], [F^L_{nmA}, F^U_{nmA}]$

Step 4: The criteria weights are aggregated by INNWA in Eq. (7) and normalized to obtain the aggregated criteria weights matrix W_A given in Eq. (12), where w_j represents the aggregated weight of the criterion j.

$$W_A = \left[w_j\right]_{1*m} \tag{12}$$

Step 5: The average solution matrix AV is obtained by taking the average of the aggregated alternative evaluations x_{ijA} as given in Eq. (13):

$$AV = \left[AV_j\right]_{1*m} = \frac{1}{n}\sum_{i=1}^{n} x_{ijA} \tag{13}$$

Table 4 IVN Scale for criteria evaluation [45]

	Linguistic Terms	$\langle \boldsymbol{T}, \boldsymbol{I}, \boldsymbol{F} \rangle$
CLI	Certainly Low Importance	⟨[0.05, 0.25], [0.6, 0.7], [0.75, 0.95]⟩
VLI	Very Low Importance	⟨[0.15, 0.35], [0.5, 0.6], [0.65, 0.85]⟩
LI	Low Importance	⟨[0.25, 0.45], [0.4, 0.5], [0.55, 0.75]⟩
BAI	Below Average Importance	⟨[0.35, 0.55], [0.3, 0.4], [0.45, 0.65]⟩
AI	Average Importance	⟨[0.40, 0.60], [0.1, 0.2], [0.40, 0.60]⟩
AA	Above Average Importance	⟨[0.45, 0.65], [0.3, 0.4], [0.35, 0.55]⟩
HI	High Importance	⟨[0.55, 0.75], [0.4, 0.5], [0.25, 0.45]⟩
VHI	Very High Importance	⟨[0.65, 0.85], [0.5, 0.6], [0.15, 0.35]⟩
CHI	Certainly High Importance	⟨[0.75, 0.95], [0.6, 0.7], [0.05, 0.25]⟩

Step 6: Each alternative is classified as either positively positioned or negatively positioned to the average solution AV_j with respect to each criterion. Positively positioned alternatives signify a superior performance than the average solution in terms of a criterion and contrarily, the negatively positioned alternatives indicate a worse than the average performance. The positive distance to average (PDA) of a positively positioned alternative must be positive and negative distance to average (NDA) must be zero. Contrarily, for the negatively positioned alternatives PDA must be zero and NDA must be positive. The calculation of the positive and negative distance to the average matrices (PDA and NDA) are modified by eliminating the neutrosophic subtraction to preserve the characteristics of IVNNs and to avoid negative numbers in the IVN parameters. The PDA and NDA are calculated as defined in Eqs. (14) and (15) based on the criterion type, respectively. The Euclidian distance is calculated if the difference between the deneutrosophicated aggregated alternative performance $K\left(x_{ijA}\right)$ and the deneutrosophicated average solution AV_j is positive, otherwise it assigns zero.

$$PDA = \left[pda_{ij}\right]_{m*n} = \begin{cases} z\left(K\left(x_{ijA}\right) - K\left(AV_j\right)\right) & \text{if } j \in B, \\ z\left(K\left(AV_j\right) - K\left(x_{ijA}\right)\right) & \text{if } j \in C, \end{cases} \tag{14}$$

$$NDA = \left[nda_{ij}\right]_{m*n} = \begin{cases} z\left(K\left(AV_j\right) - K\left(x_{ijA}\right)\right) & \text{if } j \in B, \\ z\left(K\left(x_{ijA}\right) - K\left(AV_j\right)\right) & \text{if } j \in C, \end{cases} \tag{15}$$

where B and C denote the set of the benefit and cost criteria, respectively and $z(.)$ is a function defined in Eq. (10).

Step 7: The weighted total positive distance and negative distance from the average sp_i and sn_i are calculated for each alternative i by using Eqs. (16) and (17):

$$sp_i = \sum_{j=1}^{m}\left(w_j * pda_{ij}\right), \tag{16}$$

$$sn_i = \sum_{j=1}^{m}\left(w_j * nda_{ij}\right). \tag{17}$$

Step 8: The weighted total positive distance and negative distance from the average values are normalized as given in Eqs. (18) and (19):

$$nsp_i = \frac{sp_i}{Max(sp_i)}, \tag{18}$$

$$nsn_i = 1 - \frac{sn_i}{Max(sn_i)}. \tag{19}$$

Step 9: To obtain the appraisal score as_i, the average of the normalized positive distance and normalized negative distance is computed as follows:

$$as_i = \frac{1}{2}\left(nsp_i + nsn_i\right). \tag{20}$$

Step 10: The alternatives are ranked in descending order of the appraisal score.

4. Case Study

The methodology of this study consists of three phases, namely the preparation process, the application of the IVN EDAS method and the validation of results. Figure 1 illustrates the flowchart of the presented methodology. This section presents the steps of the methodology implemented for the case study.

4.1. Problem Definition

The paper aims to determine the most appropriate drone for monitoring and detection of forest fires. The drone alternatives should be evaluated with respect to multiple and conflicting criteria. Although the drone characteristics and performances based on the criteria are known as its own specifications, the actual performance of a drone under mission highly depends on the environmental circumstances. This aspect brings the need for the use of fuzzy logic. The criteria were established through research of articles and books, as well as interviews with experts in the field. The authors and the experts omitted the sub-criteria that have similar or the exact opposite meaning in order to avoid overlapping in the criteria. For instance, the charging time and the battery life have rather opposing denotations as one refers to the time during which a drone cannot operate while the other signifies its up-time. As a result, 14 sub-criteria have been identified in total and presented in Table 6.

After determining the criteria and sub-criteria, a survey was conducted among expert DMs in the field to weigh the criteria and alternatives. All DMs were given different weights according to their expertise in the process of selecting a drone for detecting forest fires. The importance weights of the experts are assigned based on their experience by the authors. Regarding the type of drones that have been selected for the evaluation in this study, the rotorcraft drones are examined. It has been found that rotorcraft (multirotor) drones tend to be better off in terms of maneuverability, hovering capability, and looser requirements on takeoff and landing than fixed-wing drones [71]. Therefore, four different drone models of multirotor type selected as potential alternatives for detecting forest fires, and their technical specifications are presented in Table 7. The information on the experts and their weights are given as follows:

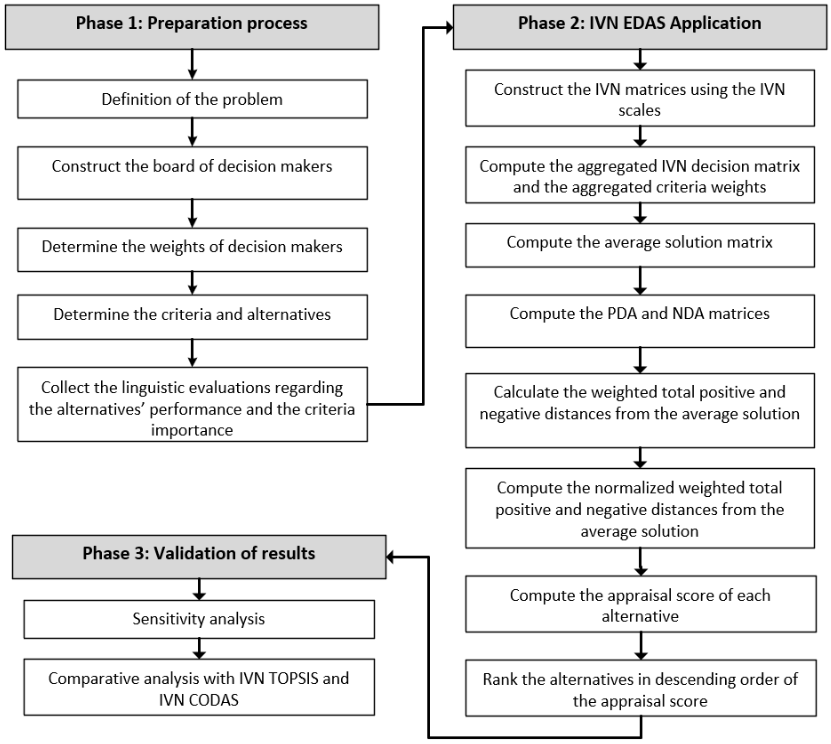

Fig. 1 Flowchart of the methodology

DM1 (40%): The first expert is a retired F16 pilot who provides drone training. He has been providing such training for about six years. He has a comprehensive knowledge on the aviation regulations, safety standards, and 10+ years of flight experience with drones.

DM2 (25%): The second expert is a fire chief. Although not fully experienced with drones, he had first-hand experience with forest fires for over 15 years. Thus, he has an in-depth knowledge of emergency response, safety protocols and fire behavior, especially how fires spread and the factors impacting the fire behavior. He mainly contributed by assessing the importance of drone attributes.

DM3 (35%): The third expert is a commercial drone user with an experience over 10 years. He has an in-depth knowledge of the technical features such as drone models, sensors, cameras, payloads, its capabilities, and the areas of drone usage. Further, he has an extensive knowledge on the sensor operation.

The description of each criterion is given as follows:

Max. Takeoff Weight (C1.1) (Benefit): It represents the maximum weight of a drone at which it is allowed to take off. In addition to its main body, for the needs of specific usage drones can be equipped with sensors, cameras, communication tools, and components such as fire extinction equipment.

Max. Horizontal Speed (C1.2) (Benefit): It expresses the maximum speed at which a drone can fly in the horizontal plane.

Max. Hover Time (C1.3) (Benefit): It is the maximum time during which a drone hovers and holds its position in the air.

Max. Flight Time (C1.4) (Benefit): It is the criterion that shows the total flight time of a drone during a single takeoff and landing.

Charging Time (C1.5) (Benefit): It indicates how long it takes a fully discharged battery of a drone to charge completely.

Max. Operating Altitude (C1.6) (Benefit): It is the maximum altitude at which a drone can operate above sea level.

Table 6 Criteria List for the drone selection for forest fires

Criteria	Sub-Criteria	References
C1. Technical Abilities	C1.1. Max. Takeoff Weight	[71, 72, 73, 74, 75]
	C1.2. Max. Horizontal Speed	[28, 59, 60, 73, 74, 76]
	C1.3. Max. Hover Time	[71]
	C1.4. Max. Flight Time	[59, 71, 73, 77]
	C1.5. Charging Time	[28, 77]
	C1.6. Max. Operating Altitude	[59, 60, 72, 73, 76, 78]
	C1.7. Wind Resistance	[79, 80]
	C1.8. Ingress Protection Rating of Drones	[77, 79]
	C1.9. Operation Frequency	[74, 81, 82]
	C1.10. Hovering Accuracy	[77]
C2. Vision-Based Technologies	C2.1. Zoom Camera	[72, 77, 78, 83]
	C2.2. Resolution	[77, 78, 84]
	C2.3.Thermal Camera Accuracy	[19, 77, 83, 85]
	C2.4. Obstacle Sensors (Range)	[28, 77, 86]

Wind Resistance (C1.7) (Benefit): The wind resistance of a drone can be affected by its weight and size. The wind resistance level is given as a value between 0 and 12. The greater the wind resistance level, the more stable can a drone operate in high-wind circumstances [80].

Ingress Protection Rating of Drones (C1.8) (Benefit): This criterion gives the IP value of a drone. IP Code (also known as International Protection Rating) categorizes the degrees of protection given in electrical enclosures against solid object infiltration, dust, accidental touch, and liquids. The IP Code consists of two digits. The first digit ranges from 1 to 6 and signifies the protection against solids, whereas the second digit ranges from 1 to 8 and indicates the resistance against liquids.

Operation Frequency (C1.9) (Benefit): It represents the frequency band that a drone uses for communication and data download.

Table 7 Technical specifications of drone alternatives

Drone Alternative	Matrice 30	Matrice 300 RTK	Matrice 210 RTK	Phantom 4 RTK
Max. Takeoff Weight (g) (C1.1)	238	930	1230	-
Max. Hor. Speed (m/s) (C1.2)	23	23	20	16
Max. Hover Time (min) (C1.3)	36	50	24	26
Max. Flight Time (min) (C1.4)	41	55	33	30
Charging Time (min) (C1.5)	30– 50	70	70	30
Max. Operating Altitude (m) (C1.6)	7000	5000	3000	6000
Wind Resistance (m/s) (C1.7)	15	15	12	10
Ingress Protection (C1.8)	IP55	IP45	IP43	IP42
Operation Frequency (C1.9)	2.4 GHz or 5 GHz	2.4 GHz or 5 GHz	2.4 - 2.48 GHz; 5.7 - 5.8 GHz	2.4 GHz or 5 GHz
Hovering Accuracy (C1.10)	V: 0.1m H: 0.3m	V: 0.1m H: 0.1m	V: 0.1m H: 0.1m	V: 0.1m H: 0.5m
Zoom Camera (C2.1)	5 m	2 m	1 m	1 m
Resolution (C2.2)	3840x2160	1920x1080	1920x1080	3840x2160
Thermal Camera Accuracy (C2.3)	±2°Cor ±2%	±5°Cor ±5%	±7°Cor ±7%	-
Obstacle Sensors (C2.4)	F: 0.6-38m U, D, B, S: 0.5-33m	F/B/L/R: 0.7-40m U/D: 0.6-30m	F: 0.7-40 m U, D, B, S: 0.7-40 m	0.7-30 m

Hovering Accuracy (C1.10) (Benefit): It indicates how stable a drone stays while hovering. This criterion is given in meters (m) by how much a drone deviates from its initial position in vertical and horizontal directions.

Zoom Camera (C2.1) (Benefit): This criterion represents how far the embedded visual camera of a drone can take a clear image.

Resolution (C2.2) (Benefit): Each visual camera has a resolution value. The resolution is one of the factors that directly affect image quality.

Thermal Camera Accuracy (C2.3) (Benefit): Thermal cameras do not need any light source for imaging. In the context of forest fires, thermal camera imaging is especially important for early detection.

Obstacle Sensors (Range) (C2.4) (Benefit): It indicates the furthest distance from which a drone can detect the obstacles.

Although the cost of a drone has been generally included as a criterion in the studies dealing with the drone selection problem for both military and civilian purposes, in this study, it has been excluded due to two reasons – first, the economic aspect must be of minor importance in disaster management as it is critical to human life and a cause of great economic and environmental losses. Second, governments do not make public procurement decisions solely based on the economic perspective, instead sustainable and strategic options are preferred.

As mentioned previously, there are interrelationships between the technical features of a drone as well as some drone attributes are highly affected by certain environmental circumstances. To give a few examples of the tradeoffs between technical internal attributes of a drone, the relationship between energy consumption and flight speed is well known. In a lower speed range, the speed does not affect the power consumption significantly. Yet in a relatively higher speed range, the power consumption increases exponentially [29]. Increased power consumption during operation means a drone requires to get charged more frequently and higher downtime which lowers the overall system efficiency. Likewise, the payload of a drone has a significant effect on power consumption. Increasing the payload of a drone rises the power consumption significantly and lowers the maximum flight time of a drone [43]. Besides the interrelation among internal features of drones, their performance is also highly affected by environmental circumstances such as temperature, wind, and precipitation. Drones with relatively small sizes and weights are prone to wind disturbances [87]. Further, it has been found that high temperature has little effect on the flight performance of a drone, but it significantly shortens the lifetime and even damages the battery, whereas extremely low temperature worsens the flight and the battery performance [88]. It can be concluded that there is a highly complex structure (1) between the internal attributes of a drone, (2) between the environmental conditions and the internal attributes of a drone. As a result, it is hard to describe and quantify the model with clear and exact terms and relations.

We conclude that the discussed problem involves uncertainties such as doubtfulness or vagueness, ambiguity, and inconsistency among its elements. The experts submit their subjective opinions based own personal experiences, background, and other individual characteristics. Further, the conflicting and complex relationships between the criteria, which were explained above, contribute to the ambiguous nature of the problem. To represent the vagueness in the decision-making process and the conflicting criteria in the problem, the IVN EDAS method is preferred.

4.2. Numerical Application

The application of the method is illustrated by the evaluation of four potential drone models, that are identified as suitable for forest surveillance and fire detection. The drone models are assessed based on the pre-determined 14 criteria by the three DMs. The steps of the methodology are given with the obtained results as follows:

Step 1: In the first step, the linguistic evaluations of the experts are collected (Table 8) and the IVN decision matrices are constructed by using the IVN scale in Table 1.

Step 2: The IVN evaluations of the alternatives are aggregated using Eq. (7). Table 9 presents the aggregated IVN matrix for Alternative 1.

Steps 3-4: The linguistic evaluations for criteria weights are collected, which are converted to IVNNs by using Table 4. The IVN matrices of the experts are then aggregated by using INNWA operator. The linguistic evaluations and the average IVN weights of the criteria are presented in Table 10.

Step 5: The average solution matrix is calculated by Eq. (13). Table 11 shows the average solution matrix.

Table 8 Linguistic evaluations of the experts

	DM1				DM2				DM3			
Criteria	AL1	AL2	AL3	AL4	AL1	AL2	AL3	AL4	AL1	AL2	AL3	AL4
C1.1	H	A	AA	L	H	BA	AA	L	L	CH	AA	BA
C1.2	H	H	AA	CH	H	H	AA	CH	CH	H	AA	CH
C1.3	CH	CH	H	AA	CH	H	AA	A	H	CH	A	A
C1.4	CH	H	AA	A	CH	H	AA	A	H	CH	A	A
C1.5	H	AA	A	A	H	AA	A	A	H	L	BA	CH
C1.6	AA	CH	A	H	AA	CH	BA	H	H	A	L	AA
C1.7	AA	AA	AA	A	AA	AA	A	BA	A	A	BA	L
C1.8	AA	CH	A	BA	AA	CH	A	BA	H	A	A	BA
C1.9	AA	H	AA	AA	AA	AA	AA	AA	H	H	H	H
C1.10	AA	H	AA	AA	AA	H	A	A	AA	A	A	A
C2.1	CH	H	AA	A	H	H	AA	A	AA	H	A	A
C2.2	H	CH	H	AA	H	CH	H	AA	CH	A	BA	BA
C2.3	H	CH	A	BA	AA	CH	A	BA	H	AA	AA	BA
C2.4	H	AA	BA	A	H	AA	H	A	H	H	H	A

Step 6: The PDA and NDA matrices are obtained and presented in Table 12. The calculation of PDA and NDA values for Alternative 1 with respect to Criterion 3, which is a benefit criterion, is as follows:

$$pda_{13} = z\big(K(x_{13A}) - K(AV_3)\big),\ nda_{13} = z\big(K(AV_3) - K(x_{13A})\big),$$
$$K(x_{13A}) = 0.9120\ ;\ K(AV_3) = 0{,}7474;\ pda_{13} = z(0.1646) = d_E,$$
$$(x_{13A}, AV_3) = 0.1344;\ nda_{13} = z\big(K(AV_3) - K(x_{13A})\big) = 0.$$

Table 9 Aggregated IVN decision matrix of Alternative 1

	$[(\boldsymbol{T^L}.\boldsymbol{T^U}).(\boldsymbol{I^L}.\boldsymbol{I^U}).(\boldsymbol{F^L}.\boldsymbol{F^U})]$
C1.1	[(0.462,0.618), (0.400,0.500), (0.329,0.487)]
C1.2	[(0.634,0.796), (0.461,0.562), (0.142,0.314)]
C1.3	[(0.693,0.853), (0.521,0.622), (0.088,0.255)]
C1.4	[(0.693,0.853), (0.521,0.622), (0.088,0.255)]
C1.5	[(0.550,0.700), (0.400,0.500), (0.250,0.400)]
C1.6	[(0.487,0.638), (0.332,0.432), (0.311,0.462)]
C1.7	[(0.433,0.600), (0.204,0.314), (0.367,0.533)]
C1.8	[(0.487,0.638), (0.332,0.432), (0.311,0.462)]
C1.9	[(0.487,0.638), (0.332,0.432), (0.311,0.462)]
C1.10	[(0.450,0.600), (0.300,0.400), (0.350,0.500)]
C2.1	[(0.618,0.786), (0.425,0.529), (0.148,0.328)]
C2.2	[(0.634,0.796), (0.461,0.562), (0.142,0.314)]
C2.3	[(0.527,0.678), (0.372,0.473), (0.272,0.423)]
C2.4	[(0.550,0.700), (0.400,0.500), (0.250,0.400)]

Table 10 Linguistic criteria evaluations and aggregated IVN criteria weights

Criteria	DM1	DM2	DM3	Aggregated criteria weights $[(T^L,T^U),(I^L,I^U),(F^L,F^U)]$
C1.1 Max. Takeoff Weight	VL	BA	BA	[(0.276,0.479), (0.368,0.470), (0.521,0.724)]
C1.2 Max. Horizontal Speed	H	A	A	[(0.465,0.669), (0.174,0.289), (0.331,0.535)]
C1.3 Max. Hover Time	L	BA	A	[(0.331,0.532), (0.229,0.343), (0.468,0.669)]
C1.4 Max. Flight Time	H	H	VH	[(0.588,0.791), (0.432,0.533), (0.209,0.412)]
C1.5 Charging Time	VL	VL	L	[(0.186,0.387), (0.462,0.563), (0.613,0.814)]
C1.6 Max. Operating Altitude	L	VH	A	[(0.427,0.644), (0.260,0.380), (0.356,0.573)]
C1.7 Wind Resistance	H	AA	AA	[(0.492,0.694), (0.337,0.437), (0.306,0.508)]
C1.8 Ingress Protection Rating of Drones	VH	VH	H	[(0.618,0.821), (0.462,0.563), (0.179,0.382)]
C1.9 Operation Frequency	A	BA	L	[(0.338,0.539), (0.214,0.328), (0.461,0.662)]
C1.10 Hovering Accuracy	VL	VL	L	[(0.186,0.387), (0.462,0.563), (0.613,0.814)]
C2.1 Zoom Camera	A	AA	H	[(0.469,0.672), (0.214,0.328), (0.328,0.531)]
C2.2 Resolution	AA	A	H	[(0.476,0.678), (0.252,0.364), (0.322,0.524)]
C2.3 Th. Camera Accuracy	VH	VH	VH	[(0.650,0.850), (0.500,0.600), (0.150,0.350)]
C2.4 Obstacle Sensors (Range)	BA	A	VL	[(0.300,0.503), (0.273,0.388), (0.497,0.700)]

Table 11 The average solution matrix

	$[(T^L,T^U),(I^L,I^U),(F^L,F^U)]$
C1.1	[(0.437,0.599), (0.327,0.433), (0.348,0.515)]
C1.2	[(0.596,0.749), (0.440,0.541), (0.198,0.353)]
C1.3	[(0.575,0.741), (0.362,0.468), (0.216,0.384)]
C1.4	[(0.540,0.712), (0.321,0.425), (0.249,0.425)]
C1.5	[(0.470,0.640), (0.266,0.374), (0.318,0.493)]
C1.6	[(0.501,0.664), (0.307,0.419), (0.289,0.455)]
C1.7	[(0.402,0.570), (0.213,0.323), (0.397,0.564)]
C1.8	[(0.474,0.644), (0.263,0.371), (0.316,0.489)]
C1.9	[(0.497,0.648), (0.342,0.443), (0.301,0.453)]
C1.10	[(0.448,0.617), (0.214,0.323), (0.351,0.519)]
C2.1	[(0.500,0.672), (0.282,0.386), (0.291,0.465)]
C2.2	[(0.550,0.711), (0.361,0.469), (0.234,0.400)]
C2.3	[(0.491,0.654), (0.322,0.426), (0.301,0.465)]
C2.4	[(0.479,0.643), (0.297,0.397), (0.319,0.483)]

Table 12 The positive distance to average and negative distance to average matrices

	PDA				*NDA*			
Criterion	AL1	AL2	AL3	AL4	AL1	AL2	AL3	AL4
C1.1	0.0446	0.1129	0	0	0	0	0.0191	0.1291
C1.2	0.0392	0	0	0.1544	0	0.0459	0.1458	0
C1.3	0.1344	0.1523	0	0	0	0	0.1111	0.1756
C1.4	0.1718	0.1141	0	0	0	0	0.1121	0.1755
C1.5	0.0973	0	0	0.0947	0	0.0797	0.1022	0
C1.6	0	0.1399	0	0.0311	0.0191	0	0.1457	0
C1.7	0.0256	0.0256	0.0089	0	0	0	0	0.0519
C1.8	0.0397	0.1659	0	0	0	0	0.1174	0.1070
C1.9	0	0.0298	0	0	0.0099	0	0.0099	0.0099
C1.10	0.0483	0.0495	0	0	0	0	0.0414	0.0414
C2.1	0.1339	0.0776	0	0	0	0	0.0722	0.1372
C2.2	0.0903	0.0989	0	0	0	0	0.0543	0.1198
C2.3	0.0390	0.1765	0	0	0	0	0.1186	0.1192
C2.4	0.0828	0.0224	0.0351	0	0	0	0	0.1329

Steps 7-10: The PDA and NDA values are weighted by the criteria weights and summed over the criteria to obtain the positive and negative weighted total distance to the average sp_i and sn_i, respectively. Then they are normalized to calculate $nsp_i$and nsn_i. The appraisal score of each alternative is calculated and the alternatives are ranked in descending order of the appraisal score.

Table 13 Weighted total distances, appraisal scores and final ranking of the alternatives

	nsp_i	nsn_i	as_i	Rank
AL1	0.7458	0.9785	0.8621	2
AL2	1	0.9191	0.9595	1
AL3	0.0299	0.1176	0.0738	4
AL4	0.1967	0	0.0983	3

The rankings presented in Table 13 demonstrate that Matrice 300 RTK (AL2) has been evaluated as the most preferable drone with an appraisal score of 0.9595 and is closely followed by Matrice 30 (AL1) with an AS of 0.8621. The minor difference of ranking scores between AL1 and AL2 should be interpreted as both drone models provide relatively comparable performances. The final ranking obtained is as follows: AL2≻AL1≻AL4≻AL3.

4.3. Sensitivity Analysis

An extensive one-at-a-time sensitivity analysis is conducted to check for the robustness of the results to the change in the criteria weights. In total 84 sets of criteria weights are built following the approach in Gorcun et al. [89]. In each scenario, the initial weight of a criterion is decreased by the predetermined modification degree υ (15%, 30%, 45%, 60%, 75%, 90%), and the weights of the rest of the criteria are increased equally while satisfying that the sum of the weights equals to 1. Figure 2 illustrates the criteria weights used in the scenarios from SC-57 to SC-70 which are formed by a 75%-modification degree, and Figure 3 shows the resulting rankings of the alternatives in the generated 84 scenarios.

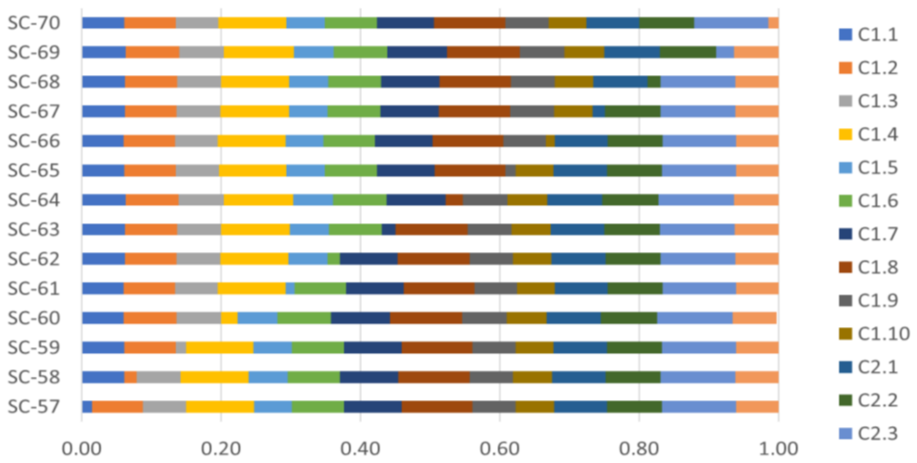

Fig. 2 The sets of criteria weights at 75% modification of each criterion

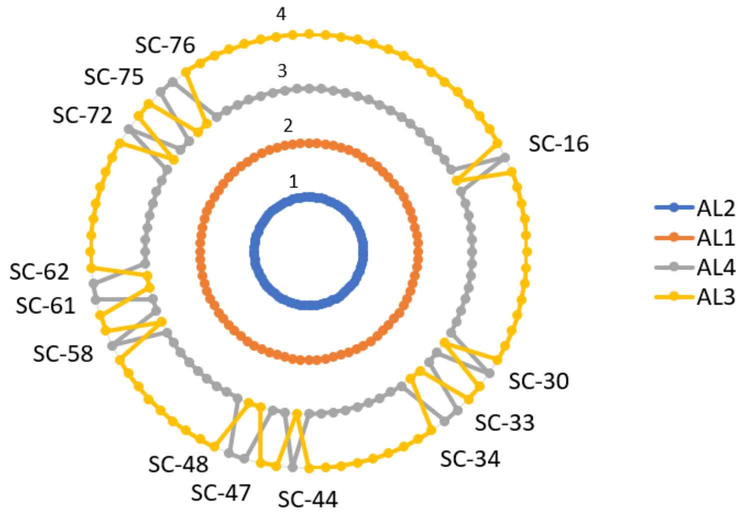

Fig. 3 Rankings of the alternatives generated through 84 scenarios

The result of the sensitivity analysis demonstrates that approximately a minimum modification by 30% of Criterion 1.2, which corresponds to scenarios SC-16, SC-30, SC-44, SC-58 and SC-72, results in the third and fourth alternatives to change ranking positions. The same result emerges under the minimum approximate modification by 45% of Criterion 1.5 and Criterion 1.6. Concludingly, in 100% of the scenarios, Alternative 2 and Alternative 1 preserved the first and second ranking positions, respectively, and in 84.5% of the scenarios (71 out of 84 scenarios) Alternative 4 has been ranked at the third and Alternative 3 at the fourth position. The sensitivity analysis indicates that the results regarding the first two ranking positions are robust against the weight changes in all criteria. The latter two positions are slightly sensitive to the changes in C1.2, C1.5 and C1.6.

4.4. Comparative Analysis

In order to check for the veracity of the method, a comparative analysis is conducted by using two MCDM methods, the interval valued neutrosophic TOPSIS, and interval valued neutrosophic CODAS methods. We preferred to apply the distance-based methods for the comparison in accordance with the method of application in this paper. For the application of IVN TOPSIS, we adopted the steps given in Karasan et al. [90]. The criteria weights are taken as given in Table 10. The Euclidian and Hamming distance measures used in this section are calculated by adopting the steps presented in the study of [91] and both equations are modified by the summation over the criteria and the division by the number of criteria in the model.

In the applied IVN TOPSIS method, first, the decision matrices are aggregated by weighting with the priorities of DMs to obtain the aggregated neutrosophic decision matrix. Then the weighted normalized decision matrix is computed by weighting the decision matrix with criteria weights. The positive ideal and the negative ideal solution are calculated as presented in Table 14. Based on the determined ideal solutions, the Euclidian distance of each alternative to the PIS and NIS is computed.

As for the second method selected for the comparative analysis, the steps of IVN CODAS are adopted from the study of [95] with minor changes from their method. The threshold parameter (θ) used in the threshold function is taken as 0.005 since the differences between the Euclidian distances of alternatives to the negative ideal solution are significantly close. To incorporate the difference of Hamming distances into the calculation, we adjusted the value of the threshold parameter. Table 15 shows the results obtained by IVN TOPSIS, IVN CODAS and IVN EDAS methods.

The IVN EDAS method gives the same ranking with the IVN TOPSIS and IVN CODAS methods indicating that the proposed IVN EDAS method provides veracious and consistent results with other distance based MCDM methods.

Table 14 IVN positive ideal solution and negative ideal solution of criteria.

	PIS	*NIS*
C1.1	[(0.027, 0.037), (0.012, 0.018), (0.01, 0.02)]	[(0.014, 0.022), (0.02, 0.025), (0.025, 0.033)]
C1.2	[(0.074, 0.089), (0.03, 0.039), (0.005,0.02)]	[(0.044, 0.059), (0.059, 0.069), (0.035, 0.049)]
C1.3	[(0.05, 0.061), (0.011, 0.018), (0.005, 0.017)]	[(0.029, 0.042), (0.038, 0.045), (0.026, 0.039)]
C1.4	[(0.056, 0.069), (0.008, 0.016), (0.007, 0.021)]	[(0.032, 0.048), (0.042, 0.05), (0.032, 0.048)]
C1.5	[(0.018, 0.024), (0.005, 0.008), (0.006, 0.013)]	[(0.012, 0.017), (0.013, 0.016), (0.013, 0.019)]
C1.6	[(0.054, 0.069), (0.018, 0.027), (0.009, 0.024)]	[(0.028, 0.042), (0.03, 0.038), (0.038, 0.052)]
C1.7	[(0.036, 0.049), (0.017, 0.026), (0.03, 0.044)]	[(0.028, 0.042), (0.019, 0.028), (0.038, 0.052)]
C1.8	[(0.052, 0.066), (0.008, 0.016), (0.008, 0.023)]	[(0.028, 0.04), (0.026, 0.036), (0.036, 0.048)]
C1.9	[(0.038, 0.049), (0.024, 0.031), (0.02, 0.031)]	[(0.035, 0.046), (0.027, 0.034), (0.023, 0.033)]
C1.10	[(0.016, 0.021), (0.005, 0.008), (0.009, 0.015)]	[(0.013, 0.019), (0.009, 0.013), (0.012, 0.018)]
C2.1	[(0.058, 0.074), (0.009, 0.019), (0.014, 0.031)]	[(0.038, 0.056), (0.04, 0.05), (0.038, 0.056)]
C2.2	[(0.06, 0.076), (0.027, 0.036), (0.009, 0.027)]	[(0.038, 0.051), (0.042, 0.051), (0.035, 0.048)]
C2.3	[(0.051, 0.064), (0.011, 0.019), (0.008, 0.021)]	[(0.027,0.038), (0.036, 0.044), (0.034, 0.046)]
C2.4	[(0.033,0.043), (0.006, 0.012), (0.015,0.024)]	[(0.024, 0.036), (0.024, 0.03), (0.024, 0.036)]

4.5 Managerial Implications

The criteria significant for the forest surveillance and fire detection have been established for the first time. In this respect, a framework has been proposed that can be utilized by the authorities and experts that are responsible from the safety and security of forests against wildfires. On the long run, the integration of drones to the forest surveillance systems can significantly reduce the costs, is more reliable and effective than the other techniques such as satellite based and static WSNs. Therefore, the adoption of the drones as the state-of-the-art technology should be considered and requires a systematic examination with real-world applications.

Table 15 Comparison of results obtained by IVN TOPSIS, IVN CODAS and IVN EDAS method

	IVN TOPSIS				IVN CODAS		IVN EDAS	
	D_i^{PIS}	D_i^{NIS}	Closeness coefficient	Rank	Relative assessment score	Rank	Appraisal score	Rank
AL1	0.0103	0.0105	0.0105	2	0.0936	2	0.8621	2
AL2	0.0084	0.0124	0.0124	1	0.1107	1	0.9595	1
AL3	0.0122	0.0088	0.0088	4	-0.1185	4	0.0738	4
AL4	0.0128	0.0093	0.0093	3	-0.0858	3	0.0983	3

5. CONCLUSION

In order to deal with forest fires, which is a major cause of deforestation, early warning systems play a crucial role to contain wildfires under control timely. Drones offer superior maneuverability and real-time surveillance capabilities in areas hard to access in comparison to other technologies. Due to the aforementioned benefits, the application of drones is utilized in the early detection systems for forest fires and the type of drones has a significant impact on the effectiveness of these systems. It is noteworthy that the performance of the detection system depends on various factors such as topological characteristics of the terrain, environmental conditions and features of drones [7]. These numerous factors have interrelationships, and some may be conflicting with one another, which can be taken into account through EDAS method.

This study is aimed at addressing the drone selection problem for forest surveillance and fire detection by using the IVN EDAS method thanks to its convenience at handling the conflicting criteria and enriched information representation by the IVN sets. This study contributes by pointing out to the gap that the drone selection problem for forest surveillance and fire detection has been sparsely addressed, by presenting an extensive literature review on the technologies deployed in forest monitoring and fire detection, and by extracting the relevant criteria through an extensive literature review and interviews with the experts in field. As a result, four drone alternatives and 14 criteria have been identified. The alternatives are then evaluated based on the proposed framework using IVN EDAS method. Moreover, a sensitivity analysis is conducted in order to check for robustness by varying the criteria weights. The veracity of the results is validated by carrying out a comparative analysis with IVN TOPSIS method and IVN CODAS method.

The results are in compliance with the study of Pamučar et al. [40] regarding the relative importance of the criteria. The criteria related to the diagnosis and monitoring are assessed as the most critical features in both studies. Further, the ability of stabilization during the flight is evaluated as the second most important in this study. The flight time and the resolution for monitoring and detection are evaluated as the third and fourth most significant criteria.

It is important to note that the results should be interpreted with caution. The MCDM methods are associated with a major limitation called the rank reversal phenomenon [65]. However, the methodology proposed in this study has not been examined for this limitation and should be checked for in future work.

Based on the findings, the set of criteria and the results should be verified with in-the-field applications and compared with the state of knowledge. In future studies, the performance of fuzzy and neutrosophic MCDM methods should be evaluated by comparing them with the software and simulation results. The criteria set might be extended by consulting more experts and representatives from the authorities. Also, the proposed framework could be implemented under other extensions of fuzzy sets for the comparison of the results.

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