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An efficient Method for Evaluation of Unmanned Aerial Vehicles: A Case Study in Livestock

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Abstract

The increasing popularity and ease of use of unmanned aerial vehicles (UAVs) have made them a thriving technology in various fields. One of their applications is in the animal revolution, where they are used to count, monitor, and detect livestock accurately, contributing to the development of the animal revolution. However, with so many types of UAVs available, it can be challenging to decide which one is most appropriate for the task at hand due to their varying characteristics. To address this issue, the suggested model is constructed utilizing neutrosophic sets to effectively manage uncertainty and deal with multi-criteria decision-making (MCDM) situations with several conflicting criteria and options. The proposed model integrates Stepwise Weight Assessment Ratio Analysis (SWARA) and the ARAS methods for evaluating the performance of UAVs in livestock based on diverse criteria and their importance, along with single-valued neutrosophic sets (SVNSs). The SWARA method is used for calculating the weight of criteria, and the ARAS method is used for ranking alternatives. An experimental case study has been established for choosing the best UAV to detect livestock using the data extracted from the thermal and multispectral UAV images.

Keywords: Livestock; Single-Valued Neutrosophic Sets; Multi-Criteria Decision Making; Uncertainty; Unmanned Aerial Vehicles.

1 | Introduction

The livestock population and its products play an important role in the development of the economy, the safety of food security, and the reduction of hunger and poverty. Therefore, the livestock population must be counted effectively and accurately to increase economic growth, based on the data collected about the number of livestock, their condition, and pasture areas. Accurate censuses and statistics play a key role in developing the livestock industry and boosting economic growth. Initially, these surveys were conducted manually by human workers and trainers [1], which is done by counting and looking at the locations where livestock gather. But, it was time-consuming and required a lot of additional resources. Furthermore, the data obtained was often inaccurate, especially with large herds, due to herders lying about the number of livestock they owned to reduce their taxes.

Recently, remote sensing techniques have been used to solve the above-mentioned problem, which collects physical data from an object without contacting it. These techniques include the use of satellites and UAVs.

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For satellites, many researchers use them for remote counting and mapping of animals' populations[2]. Large animal counting was automatically performed from high-resolution panchromatic satellite images using panchromatic 50cm imagery[3]. Nevertheless, when it comes to resolving animals as small as sheep, satellite cameras have their limitations[4]. In addition, it has limitations on the amount of data collected through satellites due to the internal storage space, To store a large amount of data, we also need to consume more and more time, in addition to the limited coverage sometimes as satellites can malfunction due to weather conditions [5].

To overcome the problems of satellites, the use of UAVs has become a promising technology that has been used in many fields, especially livestock management [6]. UAVs have recently been used to survey and detect livestock. This is due to the characteristics of UAVs, as they capture images with high accuracy, which allows for the discovery and identification of livestock, especially large herds, in addition to the data collected through UAVs. It has flexibility in terms of where data is collected and when, due to UAVs being deployed only upon request, unlike satellites that orbit the Earth regularly, which leads to repeated data collection, in addition to the low cost of UAVs [7]. UAVs were taking video footage of the pastures but counting them manually [8]. A UAV was used to count and detect livestock automatically without the need for a human operator [9]. Recently, UAVs have been used with methods based on artificial intelligence to detect and count livestock in a more advanced and accurate manner [10, 11].

Choosing the best UAV for livestock detection is a multi-attribute collective decision-making problem. A UAV for livestock detection may be selected based on the objectives and viewpoints of various stakeholders. To address this problem, a methodical approach is required to compare and evaluate UAVs according to established standards. There are often multiple considerations to consider while assessing UAVs, such as technical proficiency, UAV time, vision-based technologies, resolution, and zoom camera[12]. Therefore, to fully comprehend the UAV's capabilities, it is essential to evaluate each criterion both alone and collectively. Not all criteria are created equal, and some may be more important than others in terms of necessity. Therefore, it is crucial to determine which factors are essential to operations and modify the weighting of the evaluation appropriately. Therefore, you may determine whether trade-offs are acceptable by weighing the advantages and disadvantages of each criterion. The aforementioned problems indicate that assessing UAVs for livestock detection is a challenging MCDM task.

For using the UAV in livestock detection, the MCDM is an effective technique to evaluate it and select the best option from a set of options based on a number of criteria according to expert opinions. Several studies employed the Analytic Hierarchy Process (AHP) technique to pick the best UAV engines based on their technical qualities. The AHP technique was used to prioritize objectives and select UAVs for operations involving multiple fleets [13]. By using AHP and TOPSIS methods the best drone was chosen among the alternatives to help decision-makers in the defense area [14]. the integration of fuzzy set and TOPSIS technique used to select the best UAV [15].

Uncertain scenarios are outside the scope of fuzzy sets; they can only handle circumstances that are true or false. As a generalization of fuzzy sets, intuitionistic fuzzy sets and interval value intuitionistic fuzzy sets have been presented to overcome this issue. The intuitionistic fuzzy set, however, is still unable to address ambiguity and inconsistency in information or to articulate them. For neutrosophic sets, the notion of truth, falsity, and indeterminacy (T, I, and F) membership has been introduced. This may assist in resolving the issues raised by such data. Single-valued neutrosophic sets (SVNSs) are a particular kind of neutrosophic set, which we will use in this research.

Every prior study demonstrates the value and adaptability of MCDM techniques in assessing different aspects of UAV technology. Using MCDM methodologies, one can compare several solutions based on technical ability, efficacy, and sustainability, among other variables, to make well-informed decisions. There isn't a comprehensive study available yet that provides a method for classifying and choosing UAVs for livestock detection after considering the requirements. As a result, this study offers a way to assess UAV standards and select the most effective UAV for livestock detection.

The evaluation of UAVs used for livestock detection is presented in this study as an MCDM problem using the neutrosophic sets, ARAS and SWARA. Using neutrosophic technique on various linguistic sets and integrating it with MCDM using SWARA and ARAS methods, the goal of this research is to delve deeper into the topic of uncertainty and vagueness to determine the most appropriate UAV for livestock detection that led to the growth of the economy, assurance of food security, and decrease in poverty and hunger. To satisfy consumer demand, a variety of UAV models have been produced. These models use several criteria.

In this research, we have identified technical ability, UAV time, and vision-based technology as the primary criteria. Within technical ability, we have further considered sub-criteria such as takeoff weights, horizontal speed, and wind resistance. In the case of UAV time, we have included charging time and hover time as sub-criteria. Lastly, we have listed resolution, zoom camera, and thermal camera accuracy as sub-criteria for vision-based technology. It's significant to note that all these criteria are of benefit. The criteria that were addressed in this research are the following:

C11: Takeoff weight: It stands for the heaviest weight that a drone is permitted to take off. Drones can be customized with additional parts, such as fire extinguishing systems, sensors, cameras, and communication tools, in addition to their basic body, to meet specific operational requirements.

C12: H.speed: It describes the highest speed a drone is capable of traveling in a horizontal plane.

C13: Wind resistance: A drone's weight and size can have an impact on its wind resistance, in high-wind conditions, a drone can function more steadily with a higher amount of wind resistance.

C21: Charging time: Indicates the maximum extent the battery remains charged

C22: Hover time: It is the longest time a UAV can hover and maintain its location in the air.

C31: Resolution: One of the elements that directly influences the quality of an image is its resolution.

C32: Zoom camera: shows the maximum distance that a drone's integrated visual camera can capture a sharp image.

C33: Thermal camera accuracy: For imaging, thermal cameras don't require a light source. In particular, thermal camera imaging is crucial for early detection.

UAVs fall into the following categories depending on how many rotors they have: multi-rotary-wing and fixed-wing. There are two types of UAVs, those with fixed wings and those with rotating wings. Rotary-wing UAVs are easy to operate and maneuver since they can take off and land vertically and swiftly, hover, fly at low speeds, and take off and land in any direction. On the other hand, fixed-wing aircraft can lift forward because of their rigid wings. Although fixed-wing UAVs have an excellent flight range, an easy-to-maintain architecture, and low maintenance and repair costs, their launch and recovery require a large amount of space. It's worth mentioning that UAVs come in an enormous variety of forms, and the four varieties we will discuss are just examples. It should be noted that most UAVs are equipped with a camera or video recorder which, are used to capture aerial images and videos.

Fixed-wing (GATEWING X100) denoted as A1: is a UAV designed for aerial surveying and mapping purposes, has a high-quality camera for taking images from the air, and may be launched manually [16]. (SPREADING WINGS S1000) is the multi-rotary-wings, we denoted as A2, it has a maximum payload capacity of 6 kg and a sturdy carbon fiber structure, this professional UAV is ideal for a variety of applications, including aerial photography, mapping, surveillance, and search and rescue missions. It can fly for up to 15 minutes. It is a dependable tool for shooting aerial movies since it has retractable landing gear, GPS, and remote control. It has a maximum speed of 80 km/h and a range of up to 1.5 kilometers [17]. the OKTO XL, which we donated as A3, features include a Canon G11 camera, which is perfect for aerial photography; a 25-minute flight time; a 1.8-kg payload capacity; and the need for an observer to drive it. It moves 70 meters above the ground at a pace of one meter per second[18]. The last type of UAV in this research is PARROTAR/2.0 is the multi-rotary-wing, which we denoted as A4 it has multiple sensors, such as a 3-axis accelerometer, gyroscope, magnetometer, pressure sensor, and ultrasonic sensors to measure flying and ground height, it can operate on mobile or tablet operating systems, it has four brushless in-runner motors installed, which enable it to record video at 30 frames per second in 720 pixels[19].

The rest of this paper is organized as follows: Section 2 presents the suggested methodology for computing the criteria weights and ranking the alternatives. Section 4 presents the results of the proposed methodology. Finally, Section 4 presents the conclusions section.

2 | Methodology

To evaluate the efficiency of UAVs in precisely counting, monitoring, and detecting livestock and advancing the animal revolution, this study proposes an integrated SVNs-SWARA-ARAS technique. We are using the SWARA method of the MCDM technique to generate the weights of the main criteria and sub-criteria, which are then represented in the decision tree. Meanwhile, the ARAS method is used to rank the UAVs according to the weights obtained from the SWARA method.

We construct the decision tree as follows: Level 0 (the root) is the node criteria; Level 1 is formed by the nodes: technical ability (TA), UAV time (UT), and vision-based technology (VBT); Level 2 is formed by the nodes, takeoff weight, H.speed, wind resistance, charging time, hover time, resolution, zoom camera, and thermal camera.

Let's consider A= {A1, A2, A3, A4} to be a set of UAVs, and P (H) is the powerset of A. And the set of Criteria: C= {C1, C2, C3}, where C1 = technical ability, C2 = UAV time and C3= vision-based technology. Then C1= {C11, C12, C13} ={takeoff weight, H.speed, wind resistance}, C2={C21, C22}={ charging time, hover time} and C3={C31, C32, C33} = {resolution, zoom camera, thermal camera}. Figure 1 shows our methodology. Figure 2 shows the hierarchy tree of main and sub-criteria

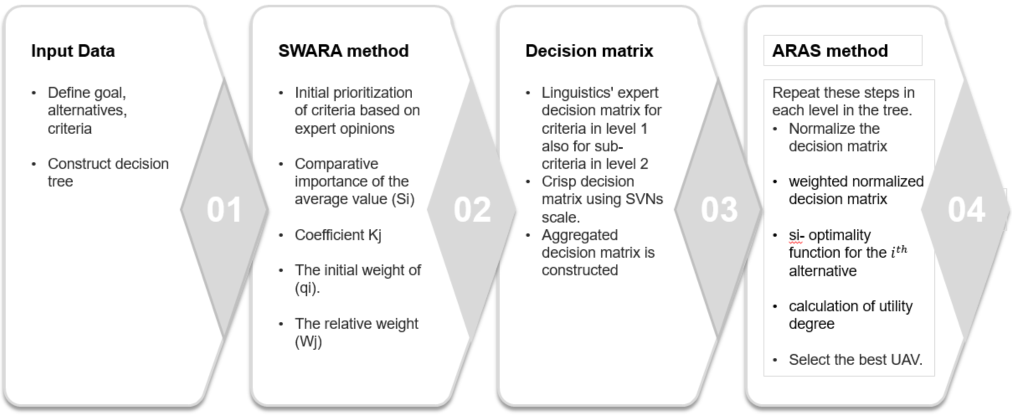

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Figure 1: Methodology steps of this study.

Table1. Single-valued Neutrosophic Scale(SVNs)[20].

Variables of Linguistic	Abbreviation	Tr	Id	F
Extremely Bad	EB	0.00	1.00	1.0
Very Very Bad	VVB	0.10	0.90	0.90
Very Bad	VB	0.20	0.85	0.80
Bad	B	0.30	0.75	.70
Medium Bad	MB	0.40	0.65	0.60
Medium	M	0.50	0.50	0.50
Medium Good	MG	0.60	0.35	0.40
Good	G	0.70	0.25	0.30
Very Good	VG	0.80	0.15	0.20
Very Very Good	VVG	0.90	0.10	0.10
Extremely Good	EG	1.00	0.00	0.00

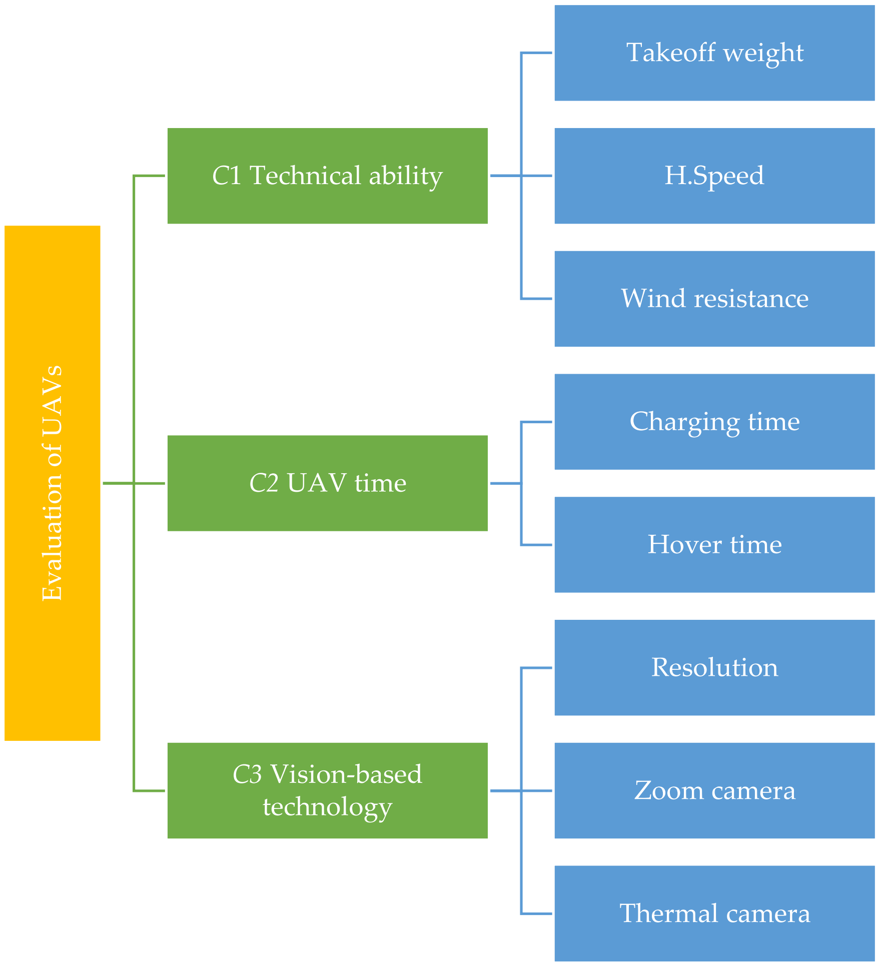

Figure 2. The hierarchy tree.

Step 1. Define the goal, criteria, and alternatives.

The goal is to select the best UAV suitable for livestock problems, first must determine the evaluation criteria $C = \{C_1, C_2, C_3\}$ and sub-criteria$\{C_{11}, C_{12}, C_{13}, C_{21}, C_{22}, C_{31}, C_{32}, C_{33},\}$, as well as identify the alternatives $A = \{A_1, A_2, \dots A_m\}$.

Step 2. Construct the hierarchy tree of our models.

Following step 1, the hierarchy tree is constructed as shown in Figure 2.

Step 3. Apply the SWARA method to calculate the weight of main criteria $\{C1, C2, C3\}$ in level 1 and sub-criteria in level 2 $\{C_{11}, C_{12}, C_{13}, C_{21}, C_{22}, C_{31}, C_{32}, C_{33},\}$ that should be considered during the process of selecting the UAVs. The SWARA method involves the following steps[21]:

- **Step 3.1**. Order the criteria from most important to least important according to the crisp value of the expert's opinion which we use the SVNs scale as shown in Table 1 to calculate it by applying the score function in equation (1) that represented as follows[20]:

$$Score\ Function = \frac{2+(Tr-F-Id)}{3} \quad (1)$$

- **Step 3.2.** We get the crisp value calculated before from Step 3.2, calculate the comparative importance of the average value S_i, beginning from the second-ordered criteria, it is necessary to find their importance, that is, how much criteria (C_j) is more important than criterion (C_{j+1}). as follows:

$$s_{i\leftrightarrow j+1} = \sum_{k=1}^{r} c_{j\leftrightarrow j+1}/r \quad (2)$$

- **Step 3.3**. Calculate coefficient (k_j) as follows:

$$K_j = \begin{cases} 1 & j = 1 \\ s_j + 1 & j > 1 \end{cases} \quad (3)$$

- **Step 3.4.** Recalculate weight q_j as follows:

$$q_j = \begin{cases} 1 & j = 1 \\ \frac{q_j - 1}{k_j} & j > 1 \end{cases} \quad (4)$$

- **Step 3.5**. Determine the weight values of the criterion with the sum that is equal to 1, as follows:

$$w_j = \frac{q_j}{\sum_{k=1}^{n} q_j} \quad (5)$$

Where w_j is the relative weight value of the criteria.

Step 4. Apply the ARAS method to rank the alternatives to select the best UAV[22]. The ARAS method involves the following steps:

- **Step 4.1**. Construct the decision matrix, based on linguistics' expert opinion, as follows:
  - Linguistic expert's Decision Matrices are constructed for evaluating criteria (C_n) in level 1 $\{C_1, C_2 \dots C_n\}$. Also, Linguistic expert's Decision Matrices are constructed for evaluating sub-criteria C_{ni} in level 2 $\{C_{1i}$, C_{2i} …., C_{ni} $\}$.
  - Constructed decision matrices are valued based on the scale of single value Neutrosophic sets (SVNs) as shown in Table 1, which is used to convert the linguistic scale into a corresponding crisp value by using the score function shown in equation 1. Decision makers may evaluate and rank the criteria objectively thanks to this process, which facilitates more data-driven decision-making
  - Create the decision matrix, based on linguistics' expert opinion in the previous step to use it in the ARAS method.

$$X = \begin{bmatrix} x_{01} & \cdots & x_{0n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \; where \; i = 0,1,2, \dots .m \, , j = 1,2,3, \dots n. \quad (6)$$

Where m is the number of alternatives, and n is the number of criteria.

  - The aggregated decision matrix is constructed as follows:

$$Y_{ij} = \frac{\sum_{j=1}^{N} x_{ij}}{E} \quad (7)$$

Where E refers to the number of experts.

- **Step 4.2**. Normalize decision matrix, represented as follows:

$$\overline{X_{ij}} = \begin{cases} \frac{y_{ij}}{\sum_{i=0}^{m} y_{ij}} & for\ benefit\ criteria \\ \frac{\sum_{i=0}^{m} y_{ij}}{y_{ij}} & for\ non-benefit\ criteria \end{cases} \quad (8)$$

- **Step 4.3**. Compute the weighted normalized decision matrix, represented as follows:

$$\widehat{x_{ij}} = \overline{X_{ij}} \times w_j \quad (9)$$

- **Step 4.4.** s_i- optimality function for the i^{th} alternative, represented as follows:

$$S_i = \sum_{j=1}^{n} \widehat{x_{ij}} \qquad for\ i = 0,1,2, \dots , m \quad (10)$$

- **Step 4.5**. Calculate of utility degree, as follows:

$$K_i = \frac{S_i}{S_0} \tag{11}$$

Where S_i, S_0 are the optimality criterion values and S_0 refers to the minimum value n S_i.

The final step is to select the best alternative based on larger K_i.

3 | Result and Discussion

This section introduces the results of the suggested methodology to select the best UAVs.

The order of main criteria and sub-criteria based on the expert's opinion:

By five experts, the main criteria and sub-criteria were ranked, after converting the linguistics' expert opinion into crisp value by SVNs scale in Table 1 using Equation 1, the obtained ranking order used in the SWARA method. As shown in Table 2 linguistics' expert opinion of main criteria and sub-criteria.

For the main criteria in level 1: the VBT criteria are in the first position (C3), the second position UT criteria (C2), and the third position TA criteria (C1).

After ranking the VBT by five experts, the sub-criteria {C31, C32, C33} in descending order become in the first position the thermal camera accuracy (C33), the resolution sub-criteria (C31) is in the second position, and zoom camera (C32) is in third position.

After ranking the UT by five experts, the sub-criteria {C21, C22} in descending order become in the first position the hover time sub-criteria (C22), and the charging time sub-criteria (C21) in the second position.

After ranking TA, the sub-criteria {C11, C12, C13} descending order become in first position (wind resistance) (C13), the H speed (C12) sub-criteria be in second position, and the takeoff weigh sub-criteria (C11) be in third position.

Table 2. Linguistics' expert opinion of main criteria and sub-criteria.

	C1	**C2**	**C3**	**C21**	**C22**	**C31**	**C32**	**C33**	**C11**	**C12**	**C13**
expert1	MB	G	EG	G	VG	MG	G	VG	G	G	EG
expert2	M	MG	VG	MG	VVG	G	G	VVG	M	VG	VVG
expert3	MB	G	VVG	G	EG	VG	MG	EG	MB	G	VVG
expert4	M	G	EG	MG	EG	VG	VG	EG	M	G	EG
expert5	M	G	EG	G	VVG	VG	VG	EG	M	G	EG

Determine (sj) comparative significance of average value for main criteria in level 1:

Table 3 shows the result of the application of equation (2) for the main criteria to get the average value (S_j) from the five experts' ideas. The next stage is the calculation of the weights of the main criteria by applying Equations (3), (4), and (5). Table 4 and Figure 3 show the weights of the main criteria in level 1 by application of the SWARA technique, where VBT (*C3*) in level 1 is the highest main criteria with a weight =0.433086332, and UT (*C2*) is the next highest criteria in level 1 with a weight = 0.343719311.

Also, determine the comparative significance of average value for sub-criteria in level 2:

- Comparative significance (S_j) of the average value for the VBT sub-criteria was calculated. Table A-1 shows the results of the application of Equation (4) for VBT sub-criteria to find the average value of (S_j) from five experts' ideas. After that, the weights of the VBT sub-criteria are calculated by applications Equations (3), (4), and (5). Table A-2 shows the weights of the VBT sub-criteria by application of the SWARA technique, where the Thermal camera accuracy *(C3)* criteria is the highest weight in the VBT sub-criteria with weight = 0.450195651.

- Comparative significance (S_j) of the average value for UT sub-criteria was calculated. Table A-3 shows the results of the application of Equation (4) for UT sub-criteria to find the average value of (S_j) from five experts' ideas. After that, the weights of UT sub-criteria are calculated by applications Equations (3), (4), and (5). Table A-4 shows the weights of UT sub-criteria by application of the SWARA technique, where the H.time *(C22)* is the highest weight in UT sub-criteria with weight = 0.609375
- Comparative significance (S_j) of the average value for the TA sub-criteria was calculated. Table A-5 shows the results of the application of equation (4) for TA sub-criteria to find the average value of (S_j) from five experts' ideas. After that, the weights of the TA sub-criteria are calculated by applications Equations (3), (4), and (5). Table A-6 shows the weights of the TA sub-criteria by application of the SWARA technique, where the wind resistance ($C13$) is the highest weight in the TA sub-criteria with weight = 0.396504642.

As shown in Figure 4, the highest weight over all trees is the Hover time with total weight = 0.209454.

Table 3. Relative importance assessment main criteria by experts' ideas.

	C3<-> C2	**C2<->C1**
expert1	0.3	0.6
expert2	0.2	0.8
expert3	0.4	0.3
expert4	0.1	0.7
expert5	0.3	0.3
average value	0.26	0.54

Table 4. Weights of main criteria by SWARA technique.

Main criteria	$s_{i\leftrightarrow j+1}$	K_j	q_j	w_j	**Final weight**
C3	----	1	1	0.433086332	43.3 %
C2	0.26	1.26	0.793650794	0.343719311	34.3 %
C1	0.54	1.54	0.515357658	0.223194358	22.3 %
			2.309008452	1	

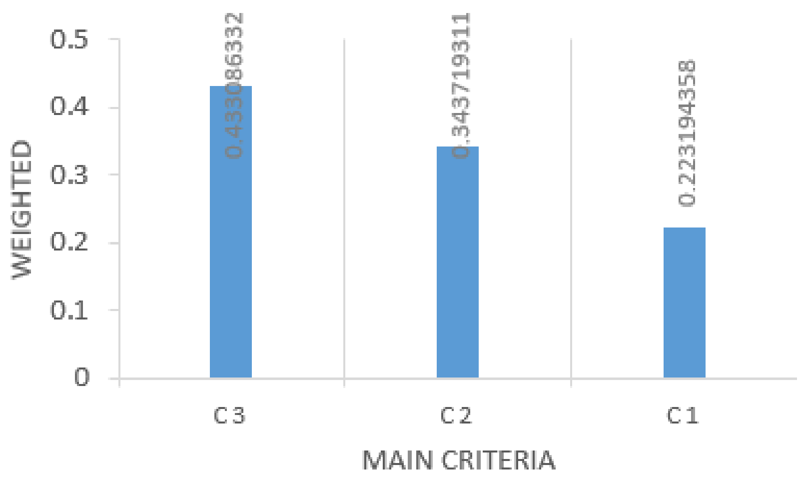

Figure 3. Weights of main criteria in level 1 by SWARA technique.

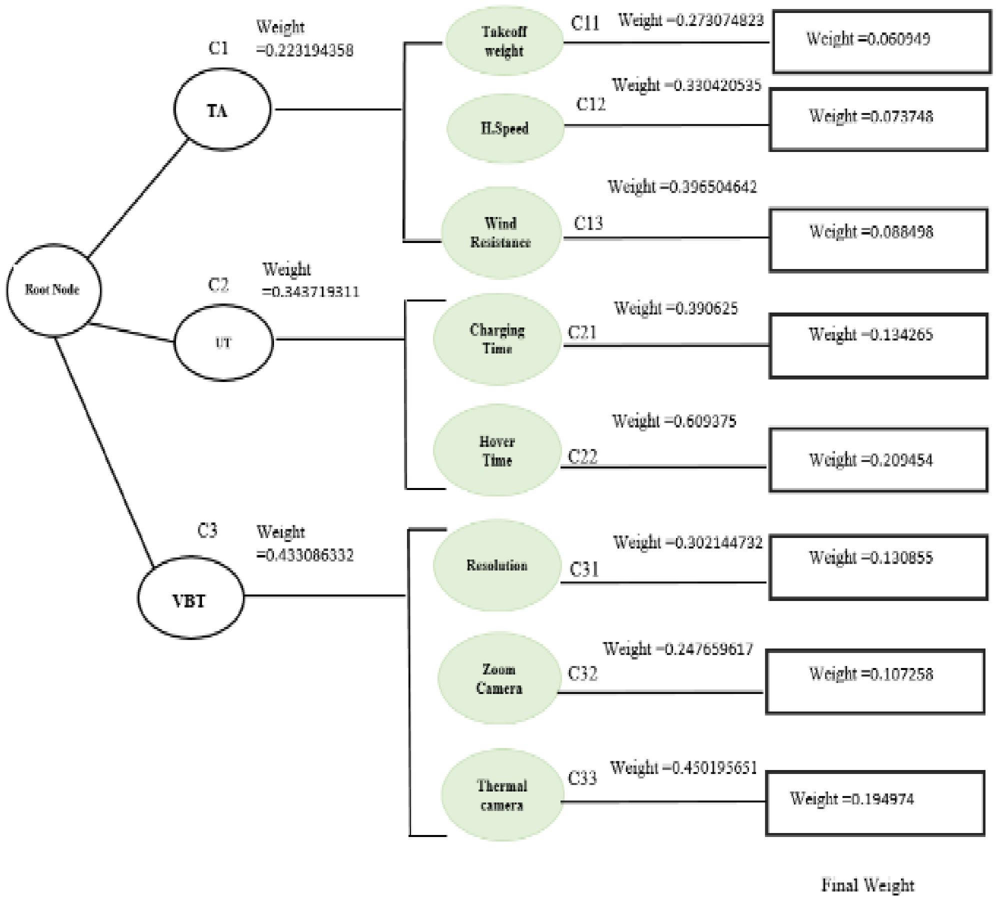

Figure 4. Weights of main criteria in level 1 by SWARA technique.

ARAS method was applied to rank the alternatives to choose the best UAV suitable for the presented problem.

First, the decision matrix must be constructed based on the expert opinion, so, in Table 5, the linguistics' expert decision matrices must be converted into crisp values by applying Eq. (1) using the SVNs scale that is illustrated in Table 1. Table 6, shows, the normalized decision matrix using Eq. (8). Table 7 shows, the weighted normalized decision matrix obtained by applying Eq. (9) using the weight of the criteria that we calculated before using the SWARA method.

The final ranking of UAVs is based on the criteria, which is illustrated in Figure 5. We demonstrated that the A_4 is the best one.

Table 5. The crisp values of the decision matrix.

	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{31}	C_{32}	C_{33}
A_1	0.246667	0.326667	0.323333	0.323333	0.37	0.2433333	0.3266667	0.3433333
A_2	0.523333	0.523333	0.523333	0.593333	0.653333	0.57	0.6133333	0.52
A_3	0.716667	0.696667	0.696667	0.756667	0.776667	0.7166667	0.7366667	0.7166667
A_4	0.813333	0.903333	0.903333	0.813333	0.87	0.7966667	0.85	0.87

Table 6. The normalized decision matrix.

	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{31}	C_{32}	C_{33}
A_1	0.107246	0.133333	0.132153	0.130027	0.138577	0.104585	0.129288	0.140136
A_2	0.227536	0.213605	0.213896	0.238606	0.244694	0.244986	0.242744	0.212245
A_3	0.311594	0.284354	0.284741	0.30429	0.290886	0.308023	0.291557	0.292517
A_4	0.353623	0.368707	0.36921	0.327078	0.325843	0.342407	0.336412	0.355102

Table 7. The weighted decision matrix.

	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{31}	C_{32}	C_{33}
A_1	0.029286	0.044056	0.052399	0.050792	0.084445	0.0316	0.032019	0.063089
A_2	0.062134	0.07058	0.084811	0.093205	0.14911	0.074021	0.060118	0.095552
A_3	0.085089	0.093956	0.112901	0.118863	0.177259	0.093068	0.072207	0.13169
A_4	0.096566	0.121829	0.146393	0.127765	0.19856	0.103456	0.083316	0.159865

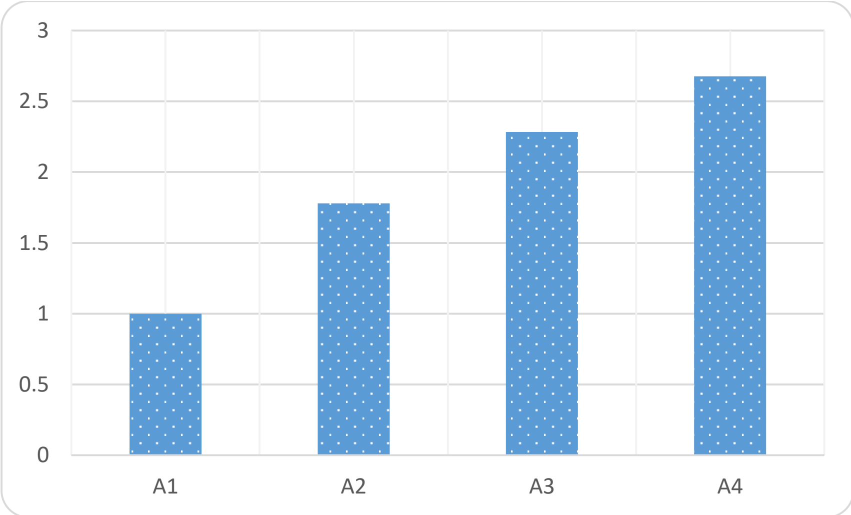

Figure 4. The rank of alternatives.

4 | Conclusion

UAVs are a growing technology because they are widely used in many different fields due to their characteristics. One of these uses is the animal revolution, which helps to further the animal revolution by precise counting, tracking, and identifying cattle. It becomes difficult to decide between the various types of suitable drones because there are many distinct types of drones, each with unique qualities. The problem is the optimal selection of the types of UAVs according to a set of criteria that fall under technical ability, UAV time, and vision-based technology. These criteria are divided into sub-criteria. Therefore, the problem was represented as a tree representing the selection tree. We proposed SWARA and the ARAS methods for evaluating the performance of UAVs in livestock based on diverse criteria and their importance, along with single-valued neutrosophic sets (SVNSs). The result of the implementation of the SWARA method indicated that the Hover time criteria are optimal based on the final value of their weight. After that, we used the ARAS method to rank the UAV type and select the best one. The result shows that PARROTAR/2.0 UAV is the best of the other candidates as it has multiple sensors, such as a 3-axis accelerometer, gyroscope, magnetometer, pressure sensor, and ultrasonic sensors to measure flying and ground height. It can operate on mobile or tablet operating systems, and it has four brushless in-runner motors installed, which enable it to record video at 30 frames per second in 720 pixels, which can detect the livestock effectively.

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Author Contribution

All authors contributed equally to this work.

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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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Appendix

Table A-1. Relative importance assessment to VBT sub- criteria in level 2 by experts' ideas.

	C33<-> C31	**C31<->C32**
expert1	.35	.25
expert2	.30	.30
expert3	.45	.20
expert4	.65	.15
expert5	.70	.20
average value	0.49	0.22

Table A-2. Weights of VBT sub- criteria in level 2 by SWARA technique.

Sub- criteria	$s_{i\leftrightarrow j+1}$	K_j	q_j	w_j	**Final weight**
C33	---	1	1	0.450195651	45.01 %
C31	0.49	1.49	0.67114094	0.302144732	30.2%
C32	0.22	1.22	0.550115524	0.247659617	24.7%

Table A-3. Relative importance assessment to UT sub- criteria in level 2 by experts' ideas.

	C22<-> C21
expert1	0.6
expert2	0.5
expert3	0.7
expert4	0.4
expert5	0.6
average value	0.56

Table A-4. Weights of UT sub- criteria in level 2 by SWARA technique.

Sub- criteria	$s_{i\leftrightarrow j+1}$	K_j	q_j	w_j	**Final weight**
C22	----	1	1	0.609375	60.9 %
C21	0.56	1.56	0.64102564	0.390625	39.0 %

Table A-5. Relative importance assessment to TA sub- criteria by experts' ideas.

	C13<-> C12	C12<->C11
expert1	0.35	0.25
expert2	0.25	0.10
expert3	0.20	0.20
expert4	0.10	0.30
expert5	0.10	0.20
average value	0.2	0.21

Table A-6. Weights of TA sub- criteria by SWARA technique.

Main criteria	$s_{i \leftrightarrow j+1}$	K_j	q_j	w_j	Final weight
C13		1	1	0.396504642	39.6 %
C12	0.2	1.2	0.833333333	0.330420535	33.0 %
C11	0.21	1.21	0.688705234	0.273074823	27.3 %
			2.522038567	1	