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A MULTI–CRITERIA DECISION–MAKING FRAMEWORK BASED ON NEUTROSOPHIC EVAMIX WITH CRITIC APPROACH FOR DRONE SELECTION PROBLEM

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ABSTRACT

In this paper, we propose a novel multi–criteria decision–making method called ***N**eutrosophic **E**VAMIX with **C**RITIC* (NE&C) ***M**ulti **C**riteria **D**ecision **M**aking* (MCDM), applied to a *drone selection* problem. The proposed method follows the basic steps of the well–known EVAMIX (EVAluation of MIXed data) method, but differs from the classical case in that attribute values are expressed using *single–valued neutrosophic sets*. Additionally, the determination of the weights of the selection criteria is not left to the discretion of the decision–maker, but the well-known CRITIC (CRiteria Importance Through Intercriteria Correlation) method is used instead. The presented drone selection problem considers nine drone alternatives to be evaluated against thirteen independent and compensatory attributes. We believe that the proposed approach, drawing upon the expressional power of neutrosophic set theory, helps the decision–maker to develop models, which can handle uncertainties arising from various reasons such as lack of sufficient and precise information, perception differences, language variables, and personal opinions, more effectively. In this paper, our goal is to extend a widely-used integrated MCDM model (i.e., EVAMIX+CRITIC) into the domain of single valued neutrosophic sets (SVNSs) so that it can handle a larger set of uncertainties in the attribute values of features.

Keywords: Single valued neutrosophic set, Drone Selection, Fuzzy logic, CRITIC method, Neutrosophic CRITIC method, EVAMIX method, Neutrosophic EVAMIX method, Multi criteria decision making, MCDM, Attribute value Uncertainty.

1. INTRODUCTION

Drones are unmanned aerial vehicles (UAVs) piloted either remotely by humans or by a computer. Initially developed for military purposes, the rapid advances in the instrumentation systems have resulted in an increasing uptake of this technology across various public and private sectors creating an ever–expanding global market especially for off–the–shelf civilian drones. Today, getting more and more accessible and affordable, drones are used in a plethora of fields such as journalism, sports, travel, marketing, agriculture, cargo, racing, health, mapping, fashion, emergency aid and communication. Consequently, many drone 4alternatives with substantial differences in size, price, features and capabilities are offered to individual users, which they can choose from in accordance with their own budgets, and the constraints of the applications involved. However, in order to select the most suitable drone among the available alternatives, many conflicting criteria such as camera, flight distance, weight, size, battery, maximum speed, flight time, and aesthetics should be considered. For this reason, drone selection problem is one of the contemporary decision-making applications that can benefit from multi–criteria decision–making (MCDM) techniques.

MCDM techniques can be classified into two broad classes, namely, Multiple Objective Decision Making (MODM) methods for *designing* the best solution and Multiple Attribute Decision Making (MADM) 5methods for *choosing* the best alternative [3]. Thus, the proposed MCDM method belongs to the MADM variety aiming to help the decision maker to choose from a finite number of alternatives or to rank a finite number of alternatives considering multiple criteria [12].

Drone selection problem involves a certain degree of uncertainty stemming from the personal opinions of the decision maker and the linguistic variables that she/he uses to express them. Where the determinations imposed by crisp sets or conventional fuzzy sets lack precision, and the provided knowledge is insufficient to locate the source of the inaccuracy, neutrosophic set offers an alternative solution. In this work, we employ single valued neutrosophic set theory to address uncertainty in the drone selection process. The neutrosophic EVAMIX method is used to decide the most suitable drone alternatives according to the selection criteria while the CRITIC method is used to determine the weights of the selection criteria. To the best of our knowledge, this is the first study proposed in the literature using these two methods in a complimentary way in the context of neutrosophic sets.

Handling uncertainty in any decision making process is an important topic in decision theory. The methods proposed by the fuzzy logic community usually make use of the concept of *membership degree* in its various forms to address the problems arising from uncertainty. Zadeh uses the membership degree $\mu_A(x) \in [0,1]$ to find the belonging of an element to a set [35]. The element x does not belong to the set A if its membership degree is 0, if it is 1, it is a complete member, and if it is between 0 and 1, it is a partial member. *Interval–valued* fuzzy sets are a special kind of fuzzy sets. When $\mu_A(x)$ is indeterminate, it is difficult to define it with an exact value. This situation was solved by Turksen using *spaced–valued* fuzzy sets (IVFSs) [26].

The *intuitionistic fuzzy set* is an alternative approach to define a fuzzy set in cases where the available information is insufficient for defining an ambiguous concept by means of the traditional fuzzy set [10]. The intuitionistic fuzzy set theory, which is a generalization of the fuzzy set theory first proposed by Zadeh and later developed further by Atanassov [4]. Atanassov states that the definition of the classical fuzzy set theory developed by Zadeh is correct, but it will not always give the correct answer in real life. In intuitionistic fuzzy set theory, the degree to which an element is a member of a set is specified by the *degree of non–membership* and the *degree of hesitation*. In a fuzzy set, the degree of belonging of an element to the set is $\mu_A(x)$, while the degree of not belonging to the set is $1-\mu_A(x)$. Thus, the degrees of belonging and non–belonging sum up to 1. However, this approach is not an effective method in dealing with uncertainty in real life applications when the sum of the degrees of belonging and non–belonging can be less than one. Let X be a nonempty set. The intuitionistic fuzzy set A is expressed by $A=\{\langle x,\mu_A(x),\sigma_A(x)\rangle : x \in X\}$ where for all $x \in X$, $\mu_A : X \to [0,1]$ and $\sigma_A : X \to [0,1]$ with the condition $0 \le \mu_A(x)+\sigma_A(x) \le 1$. In the intuitionistic fuzzy set theory, there is a *hesitation index* π_A in addition to the degree of membership and non–membership. The hesitation index indicates the level of hesitation whether any x element belongs to the set A or not. The degree of hesitation reflects an expert's indecision or lack of knowledge on a particular topic.

$$\pi_A(x) = 1 - \mu_A(x) - \sigma_A(x), \qquad 0 \le \pi_A(x) \le 1$$

If the degree of hesitation $\pi_A(x)$ is small, the information about the x element is relatively more accurate. If the degree of hesitation $\pi_A(x)$ is large, information about the x element is relatively uncertain. Information about the x element is the most certain when $\pi_A(x)$ value equals 0 (in this case, the intuitionistic fuzzy set becomes the fuzzy set [4]). According to Atanassov, the true membership value of an element determined according to human experience cannot be always exact. Therefore, a third parameter, namely the degree of hesitation, is needed to minimize decision–making errors.

Liu and Liao [13] and Yu and Liao [34] conducted a bibliometric analysis on research on fuzzy decision and a scientometric review on IFS studies, respectively. Due to some restrictions on accuracy and inaccuracy of membership values, fuzzy sets and their extensions can only handle ambiguous information, but not unstable and inconsistent information that might actually exist. This type of information is well managed by the *neutrosophic set* (NS) where uncertainty is clearly measured and the membership of accuracy, uncertainty, and inaccuracy is independent of each other. The neutrosophic set provides a more plausible mathematical framework for dealing with unstable and inconsistent information. In the last decade, the concept of neutrosophic set and interval neutrosophic sets (INS) have been used effectively in very diverse areas such as medical diagnosis, database, topology, image processing and decision–making [6,17,31,32,33].

Smarandache first introduced the concept of *neutrosophy* as a branch of philosophy that examines the origin, nature, and scope of neutrals [21,22,24,25]. The neutrosophic set is an important tool that generalizes the concepts of classical set, fuzzy set, interval valued fuzzy set, intuitionistic fuzzy set, interval valued intuitionistic fuzzy set, contradictory set , dialectic set, paradoxist set and tautological set [22]. In the neutrosophic set approach, a phenomenon is represented by three membership values, namely *truth*(T), *indeterminacy*(I), and *falsity*(F) where the sum of T + I + F does not have to be 1 [23]. It can be equal to 1, less than 1 or greater than 1. Less than 1 means *incomplete information*, equal to 1 means *complete information*, and greater than 1 means *contradictory information*.

Neutrosophic set can be further classified into different types and the representation of Truth–Indeterminacy and Falsity membership functions according to neutrosophic set types can be given as follows:

Single Valued Neutrosophic Set: (0.2, 0.4, 0.6)

Indeterminate Neutrosophic Set: ({0.3, 0.5}, {0.2, 0.4, 0.6}, {0.8, 0.9})

Interval valued Neutrosophic Set: ([0.6, 0.7], [0.0. 0.2], [0.3, 0.6]).

Neutrosophic sets have already been used in MCDM applications. Wang proposed single valued neutrosophic sets (SVNSs) [29,30] and the entropy measurement of SVNS was introduced by Majumdar and Samant [15]. As an extension of the cross entropy of fuzzy sets, Ye defined the cross–entropy measure of SVNS as a single valued neutrosophic cross–entropy [32] and presented a multi–criteria decision–making method based on the proposed single–valued neutrosophic cross entropy. Ye also introduced the concept of simplified neutrosophic sets (SNSs) and proposed an MCDM method using aggregation operators [33]. Peng et al. described some operations of simplified neutrosophic numbers (SNNs) and developed a comparison method using the relevant research of intuitionistic fuzzy numbers [18].Drawing upon the results of these studies, the above authors developed some SNN aggregation operators and applied them to multi–criteria group decision–making (MCGDM) problems. Zhang et al. described some new operations on INSs and developed addition operators for interval–valued neutrosophic numbers [36]. Broumi and Smarandache discussed the correlation coefficient of INSs[6].

In this paper, we deviate from those previous studies that are largely based on the concept of entropy, and combine two popular methods, namely EVAMIX and CRITIC, so that they can work with single valued neutrosophic sets in a coherent manner. This approach will allow us to use a single decision matrix instead of separate decision matrices for qualitative and quantitative attributes. Also, single-valued neutrosophic sets enhance the capability of the original CRITIC method so that it can capture the information regarding the conflicting relationships between criteria better than the original CRITIC method. Consequently, it can supply the EVAMIX method with more realistic attribute weights so that it can yield better, more reasonable results for the decision maker to use.

The paper is structured as follows: Section 2 describes briefly the steps of the original CRITIC and EVAMIX methods. Section 3 describes their neutrosophic counterparts in detail. Section 4 presents a detailed case study, in which drones are selected. Lastly, section 5 contains results and discussions.

2. CRITIC AND EVAMIX METHOD PROCEDURES

The EVAMIX and CRITIC methods form the basis of the proposed method. The detailed formulations of both methods appear in [3], which we will adhere to in this work.

2.1. EVAMIX

EVAMIX method is a multi–criteria decision-making method that simultaneously examines criteria containing qualitative and quantitative attributes, which must be independent. This method was first developed by Voogd [7,8,27,28]. Later, Martel and Matarazzo developed this method even further [16]. The EVAMIX method has the following features[3]

- It is a compensatory method.
- Qualitative and quantitative attributes should be distinguished.
- The qualitative attributes do not need to be converted into quantitative attributes.

Voogd [27]postulated that the differences between offered alternatives can be summarized by means of two dominance measures: one based on the qualitative criteria and the other on the quantitative (cardinal) criteria [28]. In order to make qualitative and quantitative attribute values comparable, both measures are standardized and normalized. By weighting these standardized dominance measures using the aggregated weights of the constituent criteria a new overall dominance score can be created, which represents the degree to which an alternative is better (or worse) than another alternative. In addition, an appraisal score for each option can be calculated on the basis of this overall measure.

In the same work, Voogd also pointed out that all standardized scores should have the same directional sense, i.e., a '*higher*' score should (for instance) imply a '*better*' score. The scores of those criteria for which '*lower*' means '*better*' should therefore be transformed, for example by subtracting them from 1. Note that the rankings of the qualitative criteria should also follow the principle *'the higher, the better*' [28]

We will not repeat the full formulation of the EVAMIX, which is already provided in [2,3,28] since after the neutrosophication of the attribute values and de-neutrosophication of them through an aggregation operator, we will have a standardized and normalized decision matrix in which there is no need to differentiate between ordinal and cardinal criteria. By the same token, CRITIC method will also be simplified since the normalization step is no longer required.

Using aggregated decision matrix, we can proceed directly to compute the pair wise dominance scores of the alternatives. After the evaluation score of each alternative is found, they are ranked in descending order and the best alternative has the largest score.

2.2 CRITIC

CRITIC method developed by Diakoulaki et al. is used to find objective weights of the criteria [9]. This method can be used directly without needing the explicitly stated opinion of decision maker. In this method, the attributes assumed not to conflict with each other and the attributes' weights are determined using the decision matrix for obtaining objective criterion weights [14].

While determining the criteria weights, both standard deviation of the criterion and correlation among criteria are taken into account so that this method assigns higher weights to the criteria havinghigh standard deviation and low correlation with others [5]. In other words, higher value means that the relative significance of the criterion is higher for the decision-making problem.

3. NEUTROSOPHIC EVAMIX and CRITIC METHODS

The proposed method NE&C consists of a combination of two separate methods named **N**eutrosophic **E**VAMIX (NE) and **N**eutrosophic **C**RITIC (NC) methods. These methods differ from their traditional counterparts in that they use Single–valued Neutrosophic Sets (SVNSs). In the following, first, we briefly describe the neutrosophic numbers and then discuss the mechanisms through which, we use them in EVAMIX and CRITIC methods.

3.1. SINGLE–VALUED NEUTROSOPHIC SETS: PRELIMINARIES

Classical sets have definite propositions in which, whether an element belongs to the set is expressed with absolute values. Various theories have been developed to examine the uncertainties that arise from insufficient and precise information, perception differences, linguistic variables and subjective opinions. One of these theories is the neutrosophic set theory. Neutrosophic set theory encompasses other fuzzy set theories in a broader and more flexible structure, including interval–valued fuzzy set theory, intuitionistic fuzzy set theory, and interval–valued intuitionistic fuzzy set theory. Neutrosophic set theory was developed by Smarandache in 1995 for modeling uncertainty problems in cases where existing information causes confusion and inconsistency. Neutrosophic set theory makes use of three independent functions, namely, the functions of truth, falsity and indeterminacy [20]. Since it is difficult to apply Neutrosophic Sets (NSs) to practical problems in its original form, Ye reduced NSs of non–standard intervals into SNSs of standard intervals that would preserve the operations of NSs[32]. In particular, if we restrict ourselves to neutrosophic sets which can be described by three real numbers in the real unit interval [0,1], then we have a Single–valued Neutrosophic Set (SVNS) which, we will be using in this work. Inthe following, the definitions, properties and operations on SVNSs are briefly explained.

Definition(Neutrosophic Set): Let *X* be a space of points (objects), with a generic element in *X* denoted by *x*. An SVNS*A* in *X* is characterized by *truth–membership* function T_A, *indeterminacy–membership* function I_A and *falsity–membership* function F_A. For each point *x* in *X*, $T_A(x)$, $I_A(x)$, $F_A(x) \in [0,1]$. Some neutrosophic set-theoretic operations, which are as defined in [30] are summarized in Table 1, where A, B and C are all SVNS sand $x \in X$.

Table 1. Some Neutrosophic Set-Theoretic Operations.

Operation	Truth	Indeterminacy	Falsity
Complement c(A)	$T_{c(A)}(x)=F_A(x)$	$I_{c(A)}(x)=1-I_A(x)$	$F_{c(A)}(x)=T_A(x)$
Containment $A \subseteq B$	$T_A(x)\le T_B(x)$	$I_A(x)\le I_B(x)$	$F_A(x)\ge F_B(x)$
Union $C=A\cup B$	$T_C(x)=\max(T_A(x),T_{\mathbf{B}}(x))$	$I_C(x)=\max(I_A(x),I_{\mathbf{B}}(x))$	$F_C(x)=\min(F_A(x),F_{\mathbf{B}}(x))$

Intersection $C = A \cap B$	$T_C(x) = \min(T_A(x), T_B(x))$	$I_C(x) = \max(I_A(x), I_B(x))$	$F_C(x) = \max(F_A(x), F_B(x))$
Difference $C = A \setminus B$	$T_C(x) = \min(T_A(x), F_B(x))$	$I_C(x) = \min(I_A(x), 1 - I_B(x))$	$F_C(x) = \max(F_A(x), T_B(x))$

3.2. NEUTROSOPHIC EVAMIX

In the traditional EVAMIX method, qualitative and quantitative attributes should be distinguished and qualitative attributes do not need to be converted into quantitative attributes. Consequently, qualitative and quantitative attributes are organized into separate decision matrices and the weights of the criteria are requested from the decision maker. Our approach differs from the standard method in following respects:

1. In order to obtain (T,I,F) triplets for each attribute value in a given problem, we construct triplet lookup tables that are indexed by linguistic hedges. The way these tables are constructed depends on the characteristics of the Universe of Discourse (UoD) for the attribute since it could be Boolean, crisp–valued, interval–valued or may contain missing values. How these cases are handled is illustrated in detail using the example in the case study section.
2. After (T,I,F) triplets are determined, the decision matrix is separated into three matrices, one composed of solely T values, one for solely I values and one for F values. Since NS theory states that these values are independent of each other.
3. To combine the results from this triplet, we use the aggregation operator [T+(1–F)+(1–I)]/3], proposed specifically for NSs in the literature [18].
4. In the standard EVAMIX method, the determination of the criteria weights is not explicitly specified and left to the discretion of the user. They can be obtained directly from the expert or through a method that is designed for this purpose, like CRITIC. In this work, we also modified the CRITIC method so it can be used with neutrosophic triplets.

3.3 NEUTROSOPHIC CRITIC

Recently, it is claimed that the original CRITIC method has a shortcoming in properly capturing the conflicting relationships between criteria, since it merely utilizes the Pearson correlation for this purpose [11]. Since the Pearson correlation detects only the linear relationship between two criteria, two criteria with a zero Pearson correlation coefficient may not be completely independent. Thus, the validity of the weights computed by the original CRITIC method can be disputed. Improvements suggested in the literature for CRITIC method usually differ only in the data normalization techniques they employ. In this work, we used SVNSs so that CRITIC method can be used not only with crisp numerical values, but also with attributes that could be Boolean, crisp–valued, interval–valued or may contain missing values.

4. CASE STUDY

This study is about an integrated application of the Neutrosophic EVAMIX with CRITIC (NE&C) method for drone selection. Nine alternative drone models and 13 different criteria are given for consideration to the expert who will make the selection. Drone models and criteria are taken from the web page https://www.drone.net.tr/drone–modelleri/prof Professional–drone–page–4.html.

In the given problem, available drone alternatives are specified as A= {A1, A2, A3, ..., A9}. Criteria for these alternatives are stated as *Weight* (C1), *Size* (C2), *Price*(C3), *Battery* (C4),*Maximum Speed* (C5),*Camera* (C6), *Flight Distance* (C7), *Flight Time* (C8), *Obstacle Sensor* (C9), *Accident Protection* (C10), *Automatic Home*

Return (C11), *Automatic Route Tracking* (C12), and *Fixed Altitude* (C13).Accordingly, the initial decision matrix is given in Table 2. The proposed method proceeds through the following steps:

Step1: First, we construct the neutrosophic decision matrix by expressing each attribute value in the original matrix in the form of (T,I,F) triplets. To set (T,I,F) values appropriately, we organize the criteria into the following classes depending on the attribute values they assume.

a) **Boolean**: The criteria C10, C11, C12 and C13 take attribute values of Boolean nature, i.e., a feature is either "*Available*" or "*Unavailable*".Here, we interpret the attribute value as "*the degree of membership in the set of objects possessing the related feature*". In the absence of additional information to refine the membership degree any further, we simply use the triplet (1,0,0) if the feature is declared "*Available*" or the triplet (0,0,1) if the feature is declared "*Unavailable*" (some researchers use the triplet (0,1,1) for logical falsity [19].

b) **Crisp Values:** The criteria C3 (Price) and C4(Battery) take crisp attribute values, albeit with opposite polarities, i.e., stronger battery is a preferable trait while exorbitant price is not. It is clear that the higher battery power should get higher membership values if we interpret the T value of the criterion C4 as "*membership degree in the set of strong batteries*". In this universe of discourse, the available values are (2050, 2700, 2420, 1480, 5000, 4300, 4500, 1800, 2420) all expressed in mAh. Ordering in descending order, we get (5000, 4500, 4300, 2700, 2420, 2420, 2050, 1800, 1480). To obtain the T values for alternatives, a simple way is to get a list of linguistic hedges, such as (*excellent*=1,0, *very good*=0.8, …,*poor*=0.4, etc.) and decide how each alternative should be classified according to these hedges. Another option might be to set the T values relative to the best option available as (2050/5000, 2700/5000, 2420/5000, 1480/5000, 5000/5000, 4300/5000, 4500/5000, 1800/5000, 2420/5000) yielding (0.4, 0.5, 0.5, 0.3, 1.0, 0.9, 0.9, 0.4, 0.5) or more accurately (0.41, 0.54, 0.48, 0.30, 1.0, 0.86, 0.90, 0.36, 0.48) if a higher precision is required. Note that if we choose to use a single decimal digit, 2420, and 2700 mAh batteries will be treated as equals in the decision process.

   On the other hand, there is no obligation to devise a kind of formula. Considering also the properties of the intended application, we might decide power ratings below 2000 mAh are equally bad and so we do not want to introduce any difference between them. In addition, the difference between 4300 and 4500 mAh batteries might be more significant for us than the above value assignments suggest. Therefore, we decide that the triplets ought to be assigned more properly as follows: (*Very Good* = (0.9,0.1,0.2), *Good* = (0.8,0.1,0.2), *Medium* = (0.5,0.1,0.2), *Poor* = (0.3,0.1,0.2), *Very Poor* = (0.2, 0.1,0.2)). Note that we used the same I and F values for all options. The reason for this is twofold: firstly, we assume that all batteries are tested by the same technician, using the same techniques and equipment so that the indeterminacy should be uniform across all test results. Secondly, we think that (maybe wrongly) battery test procedures suffer from measurement errors to some degree, and the value of F should reflect this belief of ours.

   For the price criterion C3, we think that the cheaper, the better. However, in the problem statement the price is marked as a negative trait. Consequently, the proper interpretation of T leads to assigning the highest truth-value to the highest price and let EVAMIX properly handle them. Alternatively, we could change the price criterion to a positive trait and assign the highest truth-value to the cheapest option. Changing the price to a positive trait, our assignment is as follows: (*Very Cheap*= (0.9,0.1,0.1), *Cheap* = (0.8,0.1,0.1), *Medium* = (0.5,0.1,0.1), *Expensive*= (0.3,0.1,0.1), *Very Expensive*= (0.2, 0.1,0.1)).Note that, this assignment differs from the above in F values only. Here, we assumed (again, maybe wrongly) in this age of search engines the right price for a certain merchandise can be spotted more accurately. Otherwise, we could have used the same linguistic variables for both criteria.

c) **Attribute Values from Uneven domains:** *Camera* (C6) and *Obstacle Sensor* (C9) attributes take their attribute values from uneven domains. Considering the *Obstacle Sensor* feature, we have only Available/Unavailable information for some alternatives while additional information is supplied for others as (*One-Way*, *Three-Way*, *Five-Way*, *360 degree*). One approach to solve this problem is to assume that *Available* means *One-Way*, but assign a higher I value for the option. Otherwise, we may choose to gather more information about the product, which we choose not to do. Hence, we decided to use the following values: (*360 degree =* (0.9,0.4,0.2)*, Five-Way =* (0.6,0.4,0.2), *Three-Way=*(0.5,0.4,0.2), *One–Way=*(0.4,0.4,0.2), Available =(04,0.6,0.4), Unavailable = (0.1,0.1,0.1)). Note that, we used relatively high I values, since we do not have much faith in the information provided in this column due to the relatively sloppy way it is presented.

The *Camera* (C6) criterion presents even further complications. An inspection of the attribute values indicate that C6 more appropriately ought to be replaced with three separate criteria, namely *camera resolution*, *camera speed* expressed in fps, and *field-of-view expressed* in degrees. Again, we choose not to do any additional work to complete the missing values and use the following values for the C6 criterion with a uniform indeterminacy value I=0.2 across all options: (*Very Good* = (0.9,0.2,0.2), *Good* = (0.8,0.2,0.2), *Medium* = (0.5,0.2,0.2), *Poor* = (0.3,0.2,0.2), *Very Poor* = (0.2, 0.2,0.2)).Admittedly, assigned values are somewhat arbitrary, guided by intuition and domain knowledge only to a certain degree.

d) **Interval values:** The criteria *Weight* (C1), *Size* (C2), *Maximum Speed* (C5),*Flight Distance* (C7) and *Flight Time* (C8) are specified using numeric intervals. In this cases, we will not use the intervals per se, but set (T,I,F) values in a way to represent and order numeric intervals, albeit somewhat indirectly. Our approach will be based on the following interpretations:

- T values will be set according to the center value of the interval. Consider the Flight Distances given as [600–700 m] and [7000–8000 m] for two of the alternatives. Their central values will be 650 m, and 7500 m, respectively and since longer range is better than a shorter one, the second alternative will get a higher membership value in the set of "*drones having longer flight distances*".

- I values will be set according to the width of the interval. The wider the interval length, the more variation from the central value we will observe working with the actual product, and we do not want that. In other words, the amount of variation will be more "*indeterminate*" for larger intervals and given intervals [10–20 cm] and [5–25 cm], both with the same central value of 15, we want the aggregation operator to prefer the former to the latter. Mathematically, for the interval [a,b], where b>a, c=(a+b)/2, we calculate d=(b–a)/c(d=10/15 for the former, and d=20/15 for the latter). Since we want to prefer former to the latter, we interpret the I value as "*the alternative with the lowest variation around the central value with respect to the central value*" and assign the lowest I value to the alternative with the lowest d value by setting I = d.

- Recall that we should set F values so that "*longer flight distances*" with "*lower indeterminacy values*" should be preferred over the other alternatives. Hence we use the setting F=*max* (1, 1–(T–I)) to represent this interpretation. Another explanation of this interpretation can be stated as follows. We can postulate that the effective degree of *truth–membership* T should get weaker, as the degree of *indeterminacy–membership* I gets stronger and since we assumed that T, I, F ∈ [0,1], it is reasonable to set F=*max* (1, 1–(T–I)). Note that for (T=1, I=0), when truth is complete and accompanied by no indeterminacy, the above setting yields F=0, in agreement with our interpretation of F in our proposal. Also, for both (T=0, I=0) and (T=0, I=1) we get F=1, in accordance with the settings we used for Boolean attribute values.

- Using these guidelines, the (T,I,F) values are set as follows for the criteria having interval valued attributes. Note that, the decision maker only supplies the T values. F and I values are automatically derived from the boundary values of the related interval.
- Criterion *Weight* (C1):

Drone	*Weight (gr)*	Central Value	T	I=d	F=max(1,(1-T+I))
A1	300–350 gr	325	Very Good=1.0	50/325=0.15	0.15
A2	400–450 gr	425	Good=0.8	50/425=0.11	0.32
A3	400–450 gr	425	Good=0.8	50/425=0.11	0.32
A4	300–350 gr	325	Very Good=1.0	50/325=0.15	0.15
A4	300–350 gr	325	Very Good=1.0	50/325=0.15	0.15
A6	650–750 gr	700	Poor=0.3	50/700=0.07	0.84
A7	750–800 gr	775	Very Poor=0.2	50/775=0.06	0.86
A8	460–475 gr	467.5	Medium=0.5	15/467.5=0.03	0.53
A9	750–800 gr	775	Very Poor=0.2	50/775=0.06	0.86

- Criterion *Size* (C2):

Drone	*Size (cm)*	Central Value	T	I=d	F=max(1,(1-T+I))
A1	37–40 cm	38.5	Medium=0.5	3/38.5=0.07	0.58
A2	21–25 cm	23	Good=0.8	4/23=0.17	0.37
A3	37–40 cm	38.5	Medium=0.5	3/38.5=0.07	0.58
A4	14–15 cm	14.5	Very Good=1.0	1/14.5=0.06	0.07
A4	51–60 cm	55.5	Very Poor=0.2	9/55.5=0.16	0.96
A6	16–18 cm	17	Very Good=1.0	1/17=0.05	0.12
A7	37–40 cm	38.5	Medium=0.5	3/38.5=0.07	0.58
A8	43–45 cm	44.5	Poor=0.3	2/44.5=0.04	0.74
A9	25–27 cm	26	Good=0.8	2/26=0.07	0.28

- Criterion *Maximum Speed* (C5):

Drone	*Max. Speed (kmp)*	Central Value	T	I=d	F=max(1,(1-T+I))
A1	40–50 kmp	45	Good=0.8	5/45=0.11	0.42
A2	27–30 kmp	28.5	Poor=0.3	3/28.5=0.10	0.81
A3	35–40 kmp	37.5	Medium=0.5	3/37.5=0.08	0.63
A4	40–50 kmp	45	Good=0.8	10/45=0.22	0.42
A4	10–20 kmp	15	Very Poor=0.2	10/20=0.5	1.00
A6	50–70 kmp	60	Very Good=1.0	20/60=0.33	0.33
A7	40–50 kmp	45	Good=0.8	10/45=0.22	0.42
A8	10–20 kmp	15	Very Poor=0.2	10/15=0.66	1.00
A9	40–50 kmp	45	Good=0.8	10/45=0.22	0.42

- Criterion C7 (*Flight Distance*):

Drone	*Flight Distance (m)*	Central Value	T	I=d	F=max(1,(1-T+I))
A1	1000–1500	1250	Medium=0.5	500/1250=0.40	0.90

A2	600–700	650	Poor=0.3	100/650=0.15	0.85
A3	600–700	650	Poor=0.3	100/650=0.15	0.85
A4	3500–4000	3750	Good=0.8	500/3750=0.13	0.33
A4	100–150	125	Very Poor=0.2	50/125=0.40	1.00
A6	6500–7000	6750	Very Good=1.0	500/6750=0.07	0.07
A7	7000–8000	7500	Very Good=1.0	1000/7500=0.13	0.13
A8	250–300	275	Very Poor=0.2	50/275=0.18	0.98
A9	3500–4000	3750	Good=0.8	500/3750=0.13	0.33

- Criterion *Flight Time* (C8):

Drone	*Flight Time (min)*	Central Value	T	d	F=max(1,(1-T+I))
A1	16–18 min.	17	Poor=0.3	2/17=0.11	0.82
A2	21–25 min.	23	Medium=0.5	4/23=0.17	0.67
A3	16–16 min.	16	Poor=0.3	0/16=0	0.70
A4	15–16 min.	15.5	Poor=0.3	1/15.5=0.06	0.76
A4	10–11 min.	10.5	Very Poor=0.2	1/10.5=0.09	0.90
A6	30–31 min.	30.5	Good=0.8	1/30.5=0.03	0.23
A7	35–37 min.	36	Very Good=1.0	2/36=0.05	0.06
A8	20–21 min.	20.5	Medium=0.5	1/20.5=0.04	0.55
A9	21–25 min.	23	Medium=0.5	4/23=0.17	0.67

Step 2: By setting the (T,I,F) values as described above, we obtain the neutrosophic decision matrix given in Table 3. Next we aggregate each (T,I,F) triplet into a single vales s ∈ [0,1] using the aggregated matrix score functions(T,I,F)=[T+(1–F)+(1–I)]/3 as defined in [18].

Note that, step 1 and step 2 constitute the core of the proposed method and, upon completion, they will give us a matrix in which;

- There is no qualitative criteria left and all attribute values are represented by standardized and normalized scores, so that they can be directly compared,
- All scores have the same directional sense, i.e., a '*higher*' score implies a '*better*' score, thereby complying with the Voogd's advice that is previously mentioned.

The aggregated decision matrix is given in Table 4. Note that, all criteria are marked now as positive traits.

Step 3: The aggregated decision matrix is directly fed into the CRITIC algorithm. Skipping the normalization step in the original method, CRITIC returns the criteria weights given in Table 5.

Step 4: At this point, we are ready to continue with the original EVAMIX method, resuming at the step in which performances of all alternative pairs are compared using the following equation, forc=1 (Table 6):

$$\gamma_{ii'N} = \left[\sum_{j \in O} \left\{ w_{jN} \times \left(e_{ij} - e_{i'j} \right) \right\}^{c} \right]^{1/c} \text{; i,i'} \in \{1,\ldots,m\}, \text{j=1,...,n}$$

Step 5: The dominance scores of the alternative pairs are normalized using the following equation (Table 7):

$$d_{ii'_N} = \frac{\left(\gamma_{ii'_N} - \gamma^-\right)}{\left(\gamma^+ - \gamma^-\right)}\text{; i,i'} \in \{1,\ldots,m\}$$

Step 6: The overall dominance scores of alternative pairs are computed in the original algorithm using the following formula:

$$D_{ii'} = w_o \delta_{ii'} + w_c d_{ii'} \quad ; \quad i,i' \in \{1,\dots,m\}$$

Since there are no qualitative criteria and W_c= 1, this step becomes redundant, thus (Table 7):5

$$D_{ii'} = d_{ii'} \quad ; \quad i,i' \in \{1,\dots,m\}$$

Step 7: Results obtained above are sorted in descending order, using the following equation to find the evaluation values of EVAMIX for each alternative:

$$S_i = \left[\sum_{i'} \frac{Di'i}{Dii'} \right]^{-1} \quad ; \; i,i' \in \{1,\dots,m\}$$

Step 8: The final ranking of the alternatives are given in Table 8 as;

A7>A6>A9>A2>A3>A1>A4>A5>A8.

For comparison, we also provided results from the original EVAMIX (Table 9) and NE&C with no criteria weights applied (Table 10). In the original EVAMIX, the interval values are represented by the crisp values of interval centers, since it provides no built-in mechanism to handle intervals directly. Ranking of the alternatives are also depicted in Figure 1.

5. RESULTS AND DISCUSSION

In daily life, we come across circumstances where events are ambiguous, vague, or indistinct. When describing an event or making a decision about a situation, often imprecise statements such as *probable*, *unlikely*, *moderate*, *satisfactory*, *poor*, etc. are used. Fuzzy set theory is an approach that deals with such imprecise linguistic expressions and is considered closer to human logic. However, there is no uncertainty factor in the traditional fuzzy set theory. Hence, the concept of neutrosophic set has been introduced to provide additional capabilities to represent the various forms of uncertainty stemming from incomplete and inconsistent information that exists in the real world.

In this work, we propose a novel MCDM method, called NE&C, using a Neutrosophic version EVAMIX with CRITIC methods in a complimentary manner. The NE&C method allows us to handle not only Boolean, crisp, and interval-valued attribute values, but also attribute values coming from uneven domains, in a unified and coherent manner. In addition, the use of SVNS in the proposed method facilitated the use of CRITIC method for attribute values other than crisp numerical attribute values, which it is originally limited to. In conclusion, we can state that NE&C is an easy-to-use method that can be applied across a wide variety of decision-making problems that can reflect the preferences, priorities, uncertainty and experience of the decision-maker quite effectively towards a satisfactory solution.

Our goal in this work has been twofold. First, we used single-valued neutrosophic sets, so that it is no longer necessary to organize qualitative and quantitative attributes into separate decision matrices, as required in the original EVAMIX method. Second, we addressed some recent claims advocating that the original CRITIC method has a shortcoming in properly capturing the conflicting relationships between criteria, since it merely utilizes the Pearson correlation for this purpose. Using single-valued neutrosophic sets, we attempted to capture the information regarding the conflicting relationships between criteria better than the original CRITIC method so that it can supply the EVAMIX method with more realistic attribute weights. Thus, we believe that the integrated model proposed in this paper (Neutrosophic EVAMIX+ Neutrosophic CRITIC) can yield better support for MCDM problems across a wider set of application domains.

Table 2: Initial Decision Matrix for Drone Selection

Cn/An	+ C1	+ C2	+ C3	+ C4	+ C5	+ C6	+ C7	+ C8	+ C9	+ C10	+ C11	+ C12	+ C13
A1	300–350 gr	37–40 cm	$1.799,00	2050 mAh LİPO	40–50 kmp	4K 180D	1000–1500 m	16–18 min.	Available	Available	Available	Available	Available
A2	400–450 gr	21–25 cm	$1.999,00	2700 mAh LİPO	27–30 kmp	1080p FHD	600–700 m	21–25 min.	One way	Available	Available	Available	Available
A3	400–450 gr	37–40 cm	$2.299,00	2420 mAh LİPO	35–40 kmp	1080p FHD	600–700 m	16–16 min.	Unavailable	Available	Available	Available	Available
A4	300–350 gr	14–15 cm	$3.459,25	1480 mAh LİPO	40–50 kmp	1080p FHD	3500–4000 m	15–16 min.	Three way	Available	Available	Available	Available
A5	300–350 gr	51–60 cm	$1.216,00	5000 mAh LİPO	10–20 kmp	720p HD	100–150 m	10–11 min.	Unavailable	Available	Unavailable	Unavailable	Available
A6	650–750 gr	16–18 cm	$12.999,00	4300 mAh LİPO	50–70 kmp	4K	6500–7000 m	30–31 min.	Five way	Available	Available	Available	Available
A7	750–800 gr	37–40 cm	$5.799,00	4500 mAh LİPO	40–50 kmp	4K	7000–8000 m	35–37 min.	Unavailable	Available	Available	Available	Available
A8	460–475 gr	43–45 cm	$1.649,00	1800 mAh LİPO	10–20 kmp	1080p FHD	250–300 m	20–21 min.	Unavailable	Unavailable	Available	Unavailable	Available
A9	750–800 gr	25–27 cm	$18.750,00	2420 mAh LİPO	40–50 kmp	4K 60FPS	3500–4000 m	21–25 min.	360 degree	Available	Available	Available	Available

Table 3: Neutrosophic Decision Matrix for Drone Selection

Cn/An	+ C1	+ C2	+ C3	+ C4	+ C5	+ C6	+ C7	+ C8	+ C9	+ C10	+ C11	+ C12	+ C13
A1	(1,0.15,0.15)	(0.5,0.08,0.58)	(0.8,0.1,0.1)	(0.41,0.1,0.2)	(0.8,0.22,0.42)	(0.8,0.2,0.2)	(0.5,0.40,0.90)	(0.3,0.12,0.82)	(0.4,0.6,0.4)	(1,0,0)	(1,0,0)	(1,0,0)	(1,0,0)
A2	(0.8,0.12,0.32)	(0.8,0.17,0.37)	(0.8,0.1,0.1)	(0.54,0.1,0.2)	(0.3,0.11,0.81)	(0.3,0.2,0.2)	(0.3,0.15,0.85)	(0.5,0.17,0.67)	(0.4,0.4,0.2)	(1,0,0)	(1,0,0)	(1,0,0)	(1,0,0)
A3	(0.8,0.12,0.32)	(0.5,0.08,0.58)	(0.8,0.1,0.1)	(0.48,0.1,0.2)	(0.5,0.13,0.63)	(0.3,0.2,0.2)	(0.3,0.15,0.85)	(0.3,0.00,0.70)	(0.1,0.1,0.1)	(1,0,0)	(1,0,0)	(1,0,0)	(1,0,0)
A4	(1,0.15,0.15)	(1,0.07,0.07)	(0.5,0.1,0.1)	(0.3,0.1,0.2)	(0.8,0.22,0.42)	(0.3,0.2,0.2)	(0.8,0.13,0.33)	(0.3,0.06,0.76)	(0.5,0.4,0.2)	(1,0,0)	(1,0,0)	(1,0,0)	(1,0,0)
A5	(1,0.15,0.15)	(0.2,0.16,0.96)	(0.9,0.1,0.1)	(1,0.1,0.2)	(0.2,0.67,1.00)	(0.2,0.2,0.2)	(0.02,0.40,1.00)	(0.2,0.10,0.90)	(0.1,0.1,0.1)	(1,0,0)	(0,0,1)	(0,0,1)	(1,0,0)
A6	(0.3,0.14,0.84)	(1,0.12,0.12)	(0.3,0.1,0.1)	(0.86,0.1,0.2)	(1,0.33,0.33)	(0.5,0.2,0.2)	(1,0.07,0.07)	(0.8,0.03,0.23)	(0.6,0.4,0.2)	(1,0,0)	(1,0,0)	(1,0,0)	(1,0,0)

A7	(0.2,0.06,0.86)	(0.5,0.08,0.58)	(0.5,0.1,0.1)	(0.9,0.1,0.2)	(0.8,0.22,0.42)	(0.5,0.2,0.2)	(1,0.13,0.13)	(1,0.06,0.06)	(0.1,0.1,0.1)	(1,0,0)	(1,0,0)	(1,0,0)	(1,0,0)
A8	(0.5,0.03,0.53)	(0.3,0.04,0.74)	(0.8,0.1,0.1)	(0.36,0.1,0.2)	(0.2,0.67,1.00)	(0.3,0.2,0.2)	(0.2,0.18,0.98)	(0.5,0.05,0.55)	(0.1,0.1,0.1)	(0,0,1)	(1,0,0)	(0,0,1)	(1,0,0)
A9	(0.2,0.06,0.86)	(0.8,0.08,0.28)	(0.1,0.1,0.1)	(0.48,0.1,0.2)	(0.8,0.22,0.42)	(0.9,0.2,0.2)	(0.8,0.13,0.33)	(0.5,0.17,0.67)	(0.9,0.4,0.2)	(1,0,0)	(1,0,0)	(1,0,0)	(1,0,0)

Table 4: Aggregated Decision Matrix

Cn/An	+ C1	+ C2	+ C3	+ C4	+ C5	+ C6	+ C7	+ C8	+ C9	+ C10	+ C11	+ C12	+ C13
A1	0.90	0.61	0.87	0.70	0.72	0.80	0.40	0.45	0.47	1.00	1.00	1.00	1.00
A2	0.79	0.75	0.87	0.75	0.46	0.63	0.43	0.55	0.60	1.00	1.00	1.00	1.00
A3	0.79	0.61	0.87	0.73	0.58	0.63	0.43	0.53	0.63	1.00	1.00	1.00	1.00
A4	0.90	0.95	0.77	0.67	0.72	0.63	0.78	0.49	0.63	1.00	1.00	1.00	1.00
A5	0.90	0.36	0.90	0.90	0.18	0.60	0.21	0.40	0.63	1.00	0.33	0.33	1.00
A6	0.44	0.92	0.70	0.85	0.78	0.70	0.95	0.84	0.67	1.00	1.00	1.00	1.00
A7	0.42	0.61	0.77	0.87	0.72	0.70	0.91	0.96	0.63	1.00	1.00	1.00	1.00
A8	0.65	0.50	0.87	0.69	0.18	0.63	0.35	0.63	0.63	0.33	1.00	0.33	1.00
A9	0.42	0.82	0.63	0.73	0.72	0.83	0.78	0.55	0.77	1.00	1.00	1.00	1.00

Table 5: Objective Weight of Criterion

	+ C1	+ C2	+ C3	+ C4	+ C5	+ C6	+ C7	+ C8	+ C9	+ C10	+ C11	+ C12	+ C13
w_j	0.077128	0.12271	0.059465	0.092639	0.069912	0.073761	0.06034	0.062566	0.057266	0.073858	0.072654	0.081917	0.095787
C_j	3.5035	5.5739	2.7011	4.2081	3.1757	3.3506	2.7409	2.842	2.6013	3.3549	3.3003	3.721	4.351

Table 6: Alternative Pairs Dominance Scores Matrix

Alternative Pairs $\gamma_{ii'}$	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	0	-0.058103	-0.00085246	0.049296	0.14623	-0.20882	-0.26466	0.16762	-0.20744
C2	0.058103	0	0.05725	0.1074	0.20433	-0.15071	-0.20656	0.22572	-0.14933
C3	0.00085246	-0.05725	0	0.050148	0.14708	-0.20796	-0.26381	0.16847	-0.20659
C4	-0.049296	-0.1074	-0.050148	0	0.09693	-0.25811	-0.31396	0.11832	-0.25673
C5	-0.14623	-0.20433	-0.14708	-0.09693	0	-0.35504	-0.41089	0.021393	-0.35366
C6	0.20882	0.15071	0.20796	0.25811	0.35504	0	-0.055845	0.37643	0.0013785
C7	0.26466	0.20656	0.26381	0.31396	0.41089	0.055845	0	0.43228	0.057224
C8	-0.16762	-0.22572	-0.16847	-0.11832	-0.021393	-0.37643	-0.43228	0	-0.37506
C9	0.20744	0.14933	0.20659	0.25673	0.35366	-0.0013785	-0.057224	0.37506	0

Table 7: Standardized (Overall) Dominance Scores of Alternative Pairs

Alternative Pairs $d_{ii'} = D_{ii'}$	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	0.5	0.56721	0.50099	0.44298	0.33087	0.74153	0.80612	0.30612	0.73993
C2	0.43279	0.5	0.43378	0.37578	0.26366	0.67432	0.73892	0.23892	0.67273
C3	0.49901	0.56622	0.5	0.442	0.32988	0.74054	0.80514	0.30514	0.73895
C4	0.55702	0.62422	0.558	0.5	0.38789	0.79855	0.86314	0.36314	0.79695
C5	0.66913	0.73634	0.67012	0.61211	0.5	0.91066	0.97526	0.47526	0.90907

C6	0.25847	0.32568	0.25946	0.20145	0.089338	0.5	0.56459	0.064594	0.49841
C7	0.19388	0.26108	0.19486	0.13686	0.024744	0.43541	0.5	0	0.43381
C8	0.69388	0.76108	0.69486	0.63686	0.52474	0.93541	1	0.5	0.93381
C9	0.26007	0.32727	0.26105	0.20305	0.090932	0.50159	0.56619	0.066188	0.5

Table 8: Evaluation Scores of Alternatives (NE&C with Weight ×Score Values)

Alternatives	A1	A2	A3	A4	A5	A6	A7	A8	A9
Scores	0.774121	0.771744	0.762036	0.828676	0.601928	0.846171	0.81156	0.602985	0.798919
Order	5	6	7	2	9	1	3	8	4

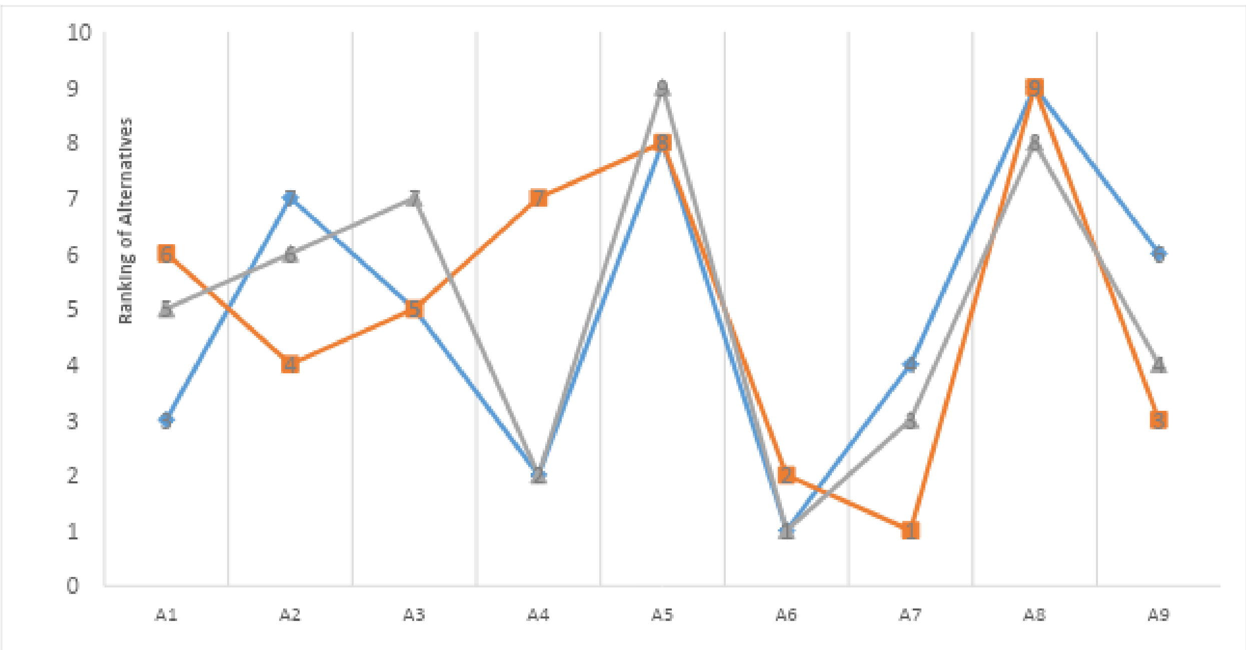
Table 9: Evaluation Scores of Alternatives (NE&C)

Alternatives	A1	A2	A3	A4	A5	A6	A7	A8	A9
Scores	0,071852	0,10247	0,072246	0,051071	0,014507	0,25696	0,39106	0	0,25455
Order	6	4	5	7	8	2	1	9	3

Table 10: Evaluation Scores of Alternatives (Original EVAMIX)

Alternatives	A1	A2	A3	A4	A5	A6	A7	A8	A9
Scores	0.17417	0.088271	0.10329	0.24998	0.035108	0.26177	0.16632	0	0.088905
Order	3	7	5	2	8	1	4	9	6

Figure 1:Ranking of Alternatives [1]


Ranking of Alternatives
10
9
8
7
6
5
4
3
2
1
0
A1
A2
A3
A4
A5
A6
A7
A8
A9

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Author Contributions

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Data Availability

The datasets generated during and/or analysed during the current study are available in the https://www.drone.net.tr/drone-modelleri/profesyonel-drone-page-4.html.