A Network Selection Algorithm for supporting Drone Services in 5G Network Architectures

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***Abstract*—Flying Ad-hoc Networks (FANETs) use 5G network access technologies to fulfill the requirements of their services. In this environment, Drone to Infrastructure (D2I) communication is supported, while each drone could use both Disaster Management (DM) and non-Disaster Management (nDM) services. Efficient network selection algorithms are required to satisfy the constraints of the used services, since the presence of DM services affects the importance of nDM services in situations where a natural disaster occurs. This paper proposes a network selection algorithm which is called Dynamic Trapezoidal Fuzzy Topsis with Adaptive Criteria Weights (DTFT-ACW). DTFT-ACW accomplishes the ranking of the candidate networks considering the importance of each service, as well as the weights of the corresponding selection criteria, as they are obtained with respect to the severity level of a natural disaster occurred. Interval-Valued Trapezoidal Fuzzy Numbers (IVTFN) are used for the criteria evaluation. Experimental results show that the suggested method outperforms existing algorithms by satisfying the constraints of DM services when a disaster becomes severe. Furthermore, DTFT-ACW eliminates the computational complexity of the network selection by considering past decisions.**

I. Introduction

Nowadays, the use of Flying Ad-hoc Networks (FANETs) [1] [2] has emerged rapidly. In a FANET environment, drones equipped with computational and network resources, communicate with each other through Drone to Drone (D2D) [3] communication, as well as with 5G network infrastructures through Drone to Infrastructure (D2I) [4] communication.

The main key enabling technologies for the 5G networks include the Cloud Computing (CC) [5] and Software Defined Networking (SDN) [6]. Indicativelly, a Cloud infrastructure can offer modern services to the FANET through D2I communication, for both disaster and non-disaster management situations. Disaster Management (DM) services refer to the manipulation of natural disasters and include Disaster-aware Information Gathering (DIG), Live Video Streaming for Emergency Manipulation (LVS-EM) and Image Transmission for Emergency Manipulation (IMT-EM). Accordingly, non-Disaster Management (nDM) services include Live Video Streaming (LVS), Image Transmission (IMT) and 3D Scanning (3DS).

The durability and the response latency of the 5G architecture could be improved by applying the operating principles of the Mobile Edge Computing (MEC) [7], resulting in the creation of a Fog infrastructure at the edge of the network. In particular, base stations are equipped with additional computational and storage resources. Furthermore, to support the communication needs of 5G terminals, dense deployments of access networks are applied, called Ultra Dense Networks (UDN) [8]. UDNs aim at the support of high data rates produced by an increased number of users. A large number of small cells, such as Femtocells, is deployed inside the network coverage area in order to increase the overall capacity of the access network [9] [10]. However, in a FANET environment drones obtain very high velocities. In this case, Femtocells are considered as an inappropriate solution, due to the small time that each drone remains inside their coverage area. To address this issue, the densification of network access resources could be performed by applying the operating principles of Massive Multiple Input Multiple Output (Massive MIMO) [11]. Specifically, Massive MIMO can be applied to an infrastructure of Macrocells, instead of using dense deployments of Femtocells with few antennas installed in each.

Regarding the Massive MIMO architectural design, 3GPP has specified the Full-Dimension MIMO (FD-MIMO) as part of the LTE-A Pro technology [12]. FD-MIMO enables the use of tens of antennas in each LTE-A Pro eNB [13].

The drones should always obtain connectivity to the best network, in order the requirements of their services to be fulfilled. Therefore, the design of efficient network selection schemes is required. In general, Multi Attribute Decision Making (MADM) methods are used to select the best alternative among candidate networks given a set of criteria with different importance weights. Widely used methods include the Analytic Hierarchy Process (AHP) [14], the Analytic network process (ANP) [15], the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [16], the Trapezoidal Fuzzy TOPSIS (TFT) [17] the Dynamic TOPSIS (DTOPSIS) [18], the Simple Additive Weighting (SAW) [14] [19], the Fuzzy SAW (FSAW) [20], the Multiplicative Exponential Weighting (MEW) [14] and the Fuzzy MEW (FMEW) [21] .

This paper proposes a network selection algorithm for supporting drone services in 5G network architectures through D2I communications. The algorithm is called Dynamic Trapezoidal Fuzzy Topsis with Adaptive Criteria Weights (DTFT-

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ACW) and performs the network selection considering the constraints of each service, as well as the Disaster Severity Level (DSL) that each drone encounters in its area.

The remainder of the paper is as follows: Section II describes the proposed algorithm. Subsequently, section III evaluates the scheme and section IV concludes the discussed work.

II. The Proposed Network Selection Algorithm

The Dynamic Trapezoidal Fuzzy Topsis with Adaptive Criteria Weights (DTFT-ACW) is proposed to accomplish the ranking of the candidate networks. The DTFT-ACW algorithm improves the TFT-ACW [22] in terms of computational complexity introduced during the network selection, resulting in the requirement of less computational resources.

The network selection performed in time t takes into consideration the previous network selection decision performed in time $t_{prev} < t$. In each time t, a list $AL(t) = \{AL_1(t), AL_2(t), \dots, AL_z(t)\}$ is constructed determining the current network alternatives. If $AL(t) = AL(t_{prev})$ then the alternatives' ranks obtained at time t_{prev} are considered, resulting in $O(n)$ complexity for the proposed algorithm. Otherwise, the methods defined by TFT-ACW algorithm are performed, resulting in $O(n^2)$ complexity, which is also introduced by the most network selection algorithms described in the research literature. In this case, similar to the TFT-ACW algorithm, the DTFT-ACW assumes that the linguistic values of criteria attributes are represented by Interval-Valued Trapezoidal Fuzzy Numbers [23]. An IVTFN is defined as $\tilde{a} = [\tilde{a}^L, \tilde{a}^U]$ consisting of the lower $\tilde{a}^L$ and the upper $\tilde{a}^U$ trapezoidal fuzzy numbers. IVTFNs replace the crisp membership values by intervals in $[0, 1]$, since the fuzzy information can be better expressed by intervals than by single values. In particular, an IVTFN can be represented as: $\tilde{a} = [\tilde{a}^L, \tilde{a}^U] = [(a_1^L, a_2^L, a_3^L, a_4^L, v^L), (a_1^U, a_2^U, a_3^U, a_4^U, v^U))]$ where: $0 \le a_1^L \le a_2^L \le a_3^L \le a_4^L \le 1$, $0 \le a_1^U \le a_2^U \le a_3^U \le a_4^U \le 1$, $0 \le v^L \le v^U \le 1$ and $\tilde{a}^L \subset \tilde{a}^U$.

A set of network selection criteria $CR(t) = \{CR_1(t), CR_2(t), \dots, CR_n(t)\}$ is considered, while $w_1, w_2, \dots, w_n$ denotes the importance weights of the respective criteria obtained from the application of the Trapezoidal Fuzzy Adaptive Analytic Network Process (TF-AANP) method described in [22]. The TF-AANP adapts the criteria weights considering the relative importance of the used services, since some services could have higher importance from the other. Specifically, the relative importance of each service s is determined using a priority vector $\tilde{\Omega}$ calculated using formula (1) where each $\tilde{\omega}_s = \left[(\omega_1^U, \omega_2^U, \omega_3^U, \omega_4^U, v_s^U); (\omega_1^L, \omega_2^L, \omega_3^L, \omega_4^L, v_s^L)\right]$ and S denotes the number of the services.

$$\tilde{\Omega} = [\ \tilde{\omega}_1 \quad \tilde{\omega}_2 \quad \dots \quad \tilde{\omega}_S\ ] \tag{1}$$

Furthermore, the TF-AANP method considers critical factors that affect the importance of each criterion, such as the severity level of a natural disaster.

The steps of the proposed network selection algorithm are as follows:

a) Construction of the decision matrix: Each $\tilde{g}_{ie}(t)$ element of the $z \times n$ decision matrix $\tilde{D}(t)$ is an IVTFN number expressing the performance of alternative AL_i for criterion CR_e. Thus

$$\tilde{D}(t) = \begin{cases} \tilde{D}(t_{prev}) \text{ , if AL(t) = AL}(t_{prev}) \\ \begin{array}{c|ccc} & CR_1(t) & \dots & CR_n(t) \\ \hline AL_1(t) & \tilde{g}_{11}(t) & \dots & \tilde{g}_{1n}(t) \\ \vdots & \vdots & \ddots & \vdots \\ AL_z(t) & \tilde{g}_{z1}(t) & \dots & \tilde{g}_{zn}(t) \end{array} \text{ , if AL(t)} \neq \text{AL}(t_{prev}) \end{cases} \tag{2}$$

where $\tilde{g}_{ie}(t) = [(g_{ie1}^L(t), g_{ie2}^L(t), g_{ie3}^L(t), g_{ie4}^L(t), v_{ie}^L(t)), (g_{ie1}^U(t), g_{ie2}^U(t), g_{ie3}^U(t), g_{ie4}^U(t), v_{ie}^U(t))]$.

In case there are S services the decision matrix includes the average of the performance values. Hence, assuming that for the s^{th} service $\tilde{g}_{iex}(t)$ is the performance of network alternative i for criterion e, the average of the performance values is given by formula (3).

$$\tilde{g}_{ie}(t) = \begin{cases} \tilde{g}_{ie}(t_{prev}) \text{ , if AL(t) = AL}(t_{prev}) \\ \sum_{s=1}^{S} (\tilde{g}_{ies}(t) \cdot \tilde{\omega}_s) \text{ , if AL(t)} \neq \text{AL}(t_{prev}) \end{cases} \tag{3}$$

b) Normalization of the decision matrix: Consider that Γ_b is the set of benefits attributes and Γ_c is the set of costs attributes. Then, the elements of the normalized decision matrix are calculated using either formula (4) or (5), where $b_e(t) = \max_i g_{ie4}^U(t)$ for each $e \in \Gamma_b$ and $c_e(t) = \min_i g_{ie4}^L(t)$ for each $e \in \Gamma_c$.

$$\tilde{g}'_{ie}(t) = \begin{cases} \tilde{g}'_{ie}(t_{prev}) \text{ , if AL(t) = AL}(t_{prev}) \\ \Big[\Big(\frac{g_{ie1}^L(t)}{b_e(t)}, \frac{g_{ie2}^L(t)}{b_e(t)}, \frac{g_{ie3}^L(t)}{b_e(t)}, \frac{g_{ie4}^L(t)}{b_e(t)}, v_{ie}^L(t)\Big), \\ \Big(\frac{g_{ie1}^U(t)}{b_e(t)}, \frac{g_{ie2}^U(t)}{b_e(t)}, \frac{g_{ie3}^U(t)}{b_e(t)}, \frac{g_{ie4}^U(t)}{b_e(t)}, v_{ie}^U(t)\Big)\Big] \text{ , if AL(t)} \neq \text{AL}(t_{prev}) \end{cases} \tag{4}$$

$$\tilde{g}'_{ie}(t) = \begin{cases} \tilde{g}'_{ie}(t_{prev}) \text{ , if AL(t) = AL}(t_{prev}) \\ \Big[\Big(\frac{c_e(t)}{g_{ie4}^L(t)}, \frac{c_e(t)}{g_{ie3}^L(t)}, \frac{c_e(t)}{g_{ie2}^L(t)}, \frac{c_e(t)}{g_{ie1}^L(t)}, v_{ie}^L(t)\Big), \\ \Big(\frac{c_e(t)}{g_{ie4}^U(t)}, \frac{c_e(t)}{g_{ie3}^U(t)}, \frac{c_e(t)}{g_{ie2}^U(t)}, \frac{c_e(t)}{g_{ie1}^U(t)}, v_{ie}^U(t)\Big)\Big] \text{ , if AL(t)} \neq \text{AL}(t_{prev}) \end{cases} \tag{5}$$

c) Construction of the weighted normalized decision matrix: The weighted normalized decision matrix is constructed by multiplying each element of the normalized decision matrix $\tilde{g}'_{ie}(t)$ with the respective weight w_e according to the formula (6).

$$\tilde{u}_{ie}(t) = \begin{cases} \tilde{u}_{ie}(t_{prev}) \text{ , if AL(t) = AL}(t_{prev}) \\ \Big[\Big(g_{ie1}'^L(t) \cdot w_e, g_{ie2}'^L(t) \cdot w_e, g_{ie3}'^L(t) \cdot w_e, g_{ie4}'^L(t) \cdot w_e, v_{ie}'^L(t)\Big), \\ \Big(g_{ie1}'^U(t) \cdot w_e, g_{ie2}'^U(t) \cdot w_e, g_{ie3}'^U(t) \cdot w_e, g_{ie4}'^U(t) \cdot w_e, v_{ie}^U(t)\Big)\Big] \\ \text{ , if AL(t)} \neq \text{AL}(t_{prev}) \end{cases} \tag{6}$$

d) Determination of the positive and negative ideal solution: The positive ideal solution is defined in formula (7), where $\bigwedge\limits_i \equiv \max_i$ in case $e \in \Gamma_b$ and $\bigwedge\limits_i \equiv \min_i$ in case $e \in \Gamma_c$. Correspondingly, the negative ideal solution is defined in formula (8), where $\bigvee_i \equiv \min_i$ in case $e \in \Gamma_b$ and $\bigvee_i \equiv \max_i$ in case $e \in \Gamma_c$.

$$\tilde{G}^{+}(t)=\begin{cases}\tilde{G}^{+}(t_{prev})\text{ , if AL(t) = AL}(t_{prev})\\ \Big[\Big(g_{ie1}^{+L}(t),g_{ie2}^{+L}(t),g_{ie3}^{+L}(t),g_{ie4}^{+L}(t),v_{ie}^{+L}(t)\Big),\\ \Big(g_{ie1}^{+U}(t),g_{ie2}^{+U}(t),g_{ie3}^{+U}(t),g_{ie4}^{+U}(t),v_{ie}^{+U}(t)\Big)\Big]=\\ \Big[\Big(\bigwedge_i u_{ie1}^{L}(t),\bigwedge_i u_{ie2}^{L}(t),\bigwedge_i u_{ie3}^{L}(t),\bigwedge_i u_{ie4}^{L}(t),v_{ie}^{L}(t)\Big),\\ \Big(\bigwedge_i u_{ie1}^{U}(t),\bigwedge_i u_{ie2}^{U}(t),\bigwedge_i u_{ie3}^{U}(t),\bigwedge_i u_{ie4}^{U}(t),v_{ie}^{U}(t)\Big)\Big]\\ \text{, if AL(t)} \neq \text{AL}(t_{prev})\end{cases} \tag{7}$$

$$\tilde{G}^{-}(t)=\begin{cases}\tilde{G}^{-}(t_{prev})\text{ , if AL(t) = AL}(t_{prev})\\ \Big[\Big(g_{ie1}^{-L}(t),g_{ie2}^{-L}(t),g_{ie3}^{-L}(t),g_{ie4}^{-L}(t),v_{ie}^{-L}(t)\Big),\\ \Big(g_{ie1}^{-U}(t),g_{ie2}^{-U}(t),g_{ie3}^{-U}(t),g_{ie4}^{-U}(t),v_{ie}^{-U}(t)\Big)\Big]=\\ \Big[\Big(\bigvee_i u_{ie1}^{L}(t),\bigvee_i u_{ie2}^{L}(t),\bigvee_i u_{ie3}^{L}(t),\bigvee_i u_{ie4}^{L}(t),v_{ie}^{L}(t)\Big),\\ \Big(\bigvee_i u_{ie1}^{U}(t),\bigvee_i u_{ie2}^{U}(t),\bigvee_i u_{ie3}^{U}(t),\bigvee_i u_{ie4}^{U}(t),v_{ie}^{U}(t)\Big)\Big]\\ \text{, if AL(t)} \neq \text{AL}(t_{prev})\end{cases} \tag{8}$$

e) Measurement of the distance of each alternative from the ideal solutions: The distances of each alternative from the positive ideal solution are evaluated using formulas (9) and (10). Likewise the distances of each alternative from the negative ideal solution are estimated using formulas (11) and (12).

$$p_{i1}^{+}(t)=\begin{cases}p_{i1}^{+}(t_{prev})\text{ , if AL(t) = AL}(t_{prev})\\ \sum_{e=1}^{n}\Big\{\frac{1}{4}\Big[\Big(u_{ie1}^{L}(t)-g_{ie1}^{+L}(t)\Big)^2+\\ \Big(u_{ie2}^{L}(t)-g_{ie2}^{+L}(t)\Big)^2+\Big(u_{ie3}^{L}(t)-g_{ie3}^{+L}(t)\Big)^2+\\ \Big(u_{ie4}^{L}(t)-g_{ie4}^{+L}(t)\Big)^2\Big]\Big\}^{\frac{1}{2}}\text{ , if AL(t)} \neq \text{AL}(t_{prev})\end{cases} \tag{9}$$

$$p_{i2}^{+}(t)=\begin{cases}p_{i2}^{+}(t_{prev})\text{ , if AL(t) = AL}(t_{prev})\\ \sum_{e=1}^{n}\Big\{\frac{1}{4}\Big[\Big(u_{ie1}^{U}(t)-g_{ie1}^{+U}(t)\Big)^2+\\ \Big(u_{ie2}^{U}(t)-g_{ie2}^{+U}(t)\Big)^2+\Big(u_{ie3}^{U}(t)-g_{ie3}^{+U}(t)\Big)^2+\\ \Big(u_{ie4}^{U}(t)-g_{ie4}^{+U}(t)\Big)^2\Big]\Big\}^{\frac{1}{2}}\text{ , if AL(t)} \neq \text{AL}(t_{prev})\end{cases} \tag{10}$$

$$p_{i1}^{-}(t)=\begin{cases}p_{i1}^{-}(t_{prev})\text{ , if AL(t) = AL}(t_{prev})\\ \sum_{e=1}^{n}\Big\{\frac{1}{4}\Big[\Big(u_{ie1}^{L}(t)-g_{ie1}^{-L}(t)\Big)^2+\\ \Big(u_{ie2}^{L}(t)-g_{ie2}^{-L}(t)\Big)^2+\Big(u_{ie3}^{L}(t)-g_{ie3}^{-L}(t)\Big)^2+\\ \Big(u_{ie4}^{L}(t)-g_{ie4}^{-L}(t)\Big)^2\Big]\Big\}^{\frac{1}{2}}\text{ , if AL(t)} \neq \text{AL}(t_{prev})\end{cases} \tag{11}$$

$$p_{i2}^{-}(t)=\begin{cases}p_{i2}^{-}(t_{prev})\text{ , if AL(t) = AL}(t_{prev})\\ \sum_{e=1}^{n}\Big\{\frac{1}{4}\Big[\Big(u_{ie1}^{U}(t)-g_{ie1}^{-U}(t)\Big)^2+\\ \Big(u_{ie2}^{U}(t)-g_{ie2}^{-U}(t)\Big)^2+\Big(u_{ie3}^{U}(t)-g_{ie3}^{-U}(t)\Big)^2+\\ \Big(u_{ie4}^{U}(t)-g_{ie4}^{-U}(t)\Big)^2\Big]\Big\}^{\frac{1}{2}}\text{ , if AL(t)} \neq \text{AL}(t_{prev})\end{cases} \tag{12}$$

Consequently, the alternatives distance from the positive and negative ideal solutions are expressed by intervals such as $[p_{i1}^{+}(t), p_{i2}^{+}(t)]$ and $[p_{i1}^{-}(t), p_{i2}^{-}(t)]$, instead of single values, as in this way less information is lost.

f) Calculation of the relative closeness: The relative closeness of the distances from the ideal solutions are calculated using formulas (13) and (14). Subsequently, the compound relative closeness is obtained using formula (15).

$$RC_{i1}(t)=\begin{cases}RC_{i1}(t_{prev})\text{ , if AL(t) = AL}(t_{prev})\\ \frac{p_{i1}^{-}(t)}{p_{i1}^{+}(t)+p_{i1}^{-}(t)}\text{ , if AL(t)} \neq \text{AL}(t_{prev})\end{cases} \tag{13}$$

$$RC_{i2}(t)=\begin{cases}RC_{i2}(t_{prev})\text{ , if AL(t) = AL}(t_{prev})\\ \frac{p_{i2}^{-}(t)}{p_{i2}^{+}(t)+p_{i2}^{-}(t)}\text{ , if AL(t)} \neq \text{AL}(t_{prev})\end{cases} \tag{14}$$

$$RC_{i}(t)=\begin{cases}RC_{i}(t_{prev})\text{ , if AL(t) = AL}(t_{prev})\\ \frac{RC_{i1}(t)+RC_{i2}(t)}{2}\text{ , if AL(t)} \neq \text{AL}(t_{prev})\end{cases} \tag{15}$$

g) Alternatives ranking: The alternative networks are ranked according to their $RC_i(t)$ values, while the best alternative is the one with the higher $RC_i(t)$ value.

III. Simulation Setup and Results

In our experiments, the 5G network architecture presented in figure 1 is simulated using the Network Simulator 3 (NS3) simulator [24]. It includes a Fog and a Cloud infrastructure. The Fog infrastructure consists of 5 LTE-A Pro Macrocells with FD-MIMO antennas. Additionally, the Cloud infrastructure includes a set of Virtual Machines (VMs) that provide both Disaster Management (DM) and non-Disaster Management (nDM) services. The DM services include Disaster-aware Information Gathering (DIG), Live Video Streaming for Emergency Manipulation (LVS-EM) and Image Transmission for Emergency Manipulation (IMT-EM). Accordingly, nDM services include Live Video Streaming (LVS), Image Transmission (IMT) and transmision of models created through 3D Scanning (3DS). A Software Defined Network (SDN) controller provides centralized control of the entire system.

Table I presents the linguistic terms and the corresponding Interval-Valued Trapezoidal Fuzzy Numbers (IVTFN) used for the criteria attributes of the available access networks. Also, table II presents the specifications of each network for each service, in terms of throughput, delay, jitter, packet loss ratio, service reliability, security and price. It should be noted that service reliability determines the ability of service constraints satisfaction and optimization of performance when a network is congested.

The case where 10 drones are moving inside the access network environment is considered. Regarding the D2I communication, each drone needs to be connected to a network which satisfies the requirements of its services, while at the same time complies with the confronted Disaster Severity Level (DSL). The DSL that each drone encounters is evaluated using the scale introduced in [25]. This scale defines 5 severity levels, called Low, Guarded, Elevated, High and Severe. The Low level refers to minimum disaster effects, while the Severe level refers to the highest ones.

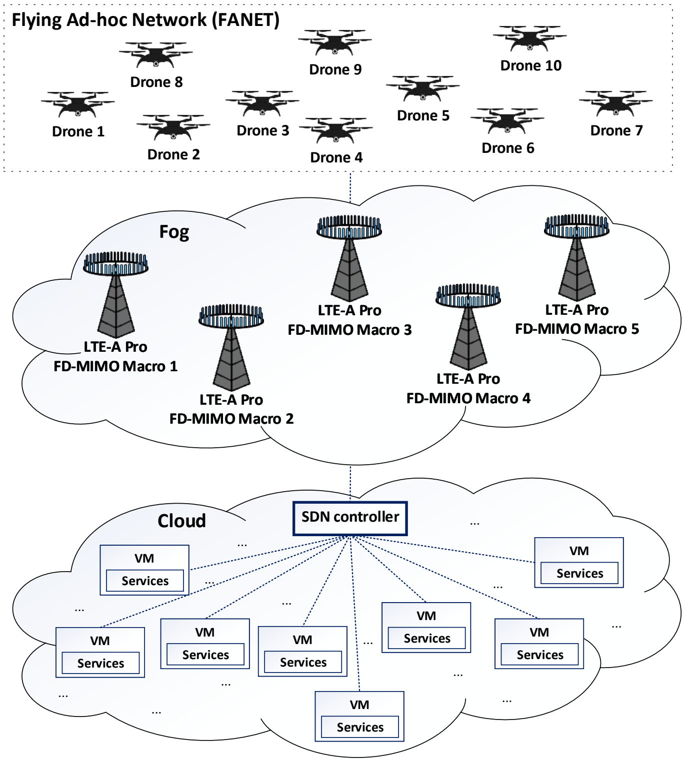

Fig. 1. The simulated topology.

TABLE I
LINGUISTIC TERMS AND THE CORRESPONDING INTERVAL-VALUED TRAPEZOIDAL FUZZY NUMBERS USED FOR THE CRITERIA ATTRIBUTES.

Linguistic term	Interval-valued trapezoidal fuzzy number
Absolutely Poor (AP)	[(0.0, 0.0, 0.06, 0.09, 0.8), (0.0, 0.0, 0.05, 0.07, 1.0)]
Very Poor (VP)	[(0.03, 0.06, 0.18, 0.21, 0.8), (0.05, 0.07, 0.17, 0.2, 1.0)]
Poor (P)	[(0.15, 0.18, 0.31, 0.34, 0.8), (0.17, 0.2, 0.3, 0.32, 1.0)]
Medium Poor (MP)	[(0.28, 0.31, 0.43, 0.46, 0.8), (0.3, 0.32, 0.42, 0.45, 1.0)]
Medium (M)	[(0.4, 0.43, 0.56, 0.59, 0.8), (0.42, 0.45, 0.55, 0.57, 1.0)]
Medium Good (MG)	[(0.53, 0.56, 0.68, 0.71, 0.8), (0.55, 0.57, 0.67, 0.7, 1.0)]
Good (G)	[(0.65, 0.68, 0.81, 0.84, 0.8), (0.67, 0.7, 0.8, 0.82, 1.0)]
Very Good (VG)	[(0.78, 0.81, 0.93, 0.96, 0.8), (0.8, 0.82, 0.92, 0.95, 1.0)]
Absolutely Good (AG)	[(0.9, 0.93, 1.0, 1.0, 0.8), (0.92, 0.95, 1.0, 1.0, 1.0)]

During the network selection process, initially the relative importance $\tilde{\omega}_{\tilde{p}s}$ of each service is considered with respect to the DSL. Figure 2 presents the importance of each service per DSL, as it is obtained using the TF-AANP [22] method. As it can be observed, the importance of DM services depends on the DSL. Indicatively, when the DSL becomes Severe, the DM services obtain higher importance than the nDM services. Accordingly, when the DSL becomes Low, the relative importance of the services is quite similar. Subsequently, the TF-AANP estimates the decision weights w_e per service type and DSL, considering the ANP network model proposed in [17]. The criteria weights for DM services are presented in figure 3. As illustrated the weights are proportional to the constraints of each service as well as to the DSL. In particular, the weight of the price criterion is low for the Severe level, resulting in a weight value which is very close to 0. Also, when the severity level is evaluated as Low, the price criterion becomes more important. Accordingly, the criteria weights for nDM services, which are also proportional to the constraints of each service, are presented in figure 4.

TABLE II
THE AVAILABLE NETWORKS.

Service	Network	Throughput	Delay	Jitter	Packet Loss	Service Reliability	Security	Price
Live Video Streaming (LVS)	LTE-A Pro FD-MIMO Macro 1	VG	G	AG	VG	VG	G	G
	LTE-A Pro FD-MIMO Macro 2	G	VG	VG	G	VG	AG	VG
	LTE-A Pro FD-MIMO Macro 3	VG	VG	VG	AG	AG	VG	AG
	LTE-A Pro FD-MIMO Macro 4	G	G	G	VG	G	G	G
	LTE-A Pro FD-MIMO Macro 5	MG	VG	VG	M	MG	VG	G
Image Transmission (IMT)	LTE-A Pro FD-MIMO Macro 1	AG	G	VG	VG	VG	AG	VG
	LTE-A Pro FD-MIMO Macro 2	AG	VG	VG	AG	AG	VG	MG
	LTE-A Pro FD-MIMO Macro 3	VG	AG	VG	G	AG	G	G
	LTE-A Pro FD-MIMO Macro 4	VG	G	G	VG	G	VG	MG
	LTE-A Pro FD-MIMO Macro 5	G	MG	G	VG	VG	MG	G
3D Scanning (3DS)	LTE-A Pro FD-MIMO Macro 1	AG	VG	VG	AG	VG	G	AG
	LTE-A Pro FD-MIMO Macro 2	AG	AG	G	AG	VG	MG	VG
	LTE-A Pro FD-MIMO Macro 3	VG	G	VG	AG	G	G	MG
	LTE-A Pro FD-MIMO Macro 4	VG	G	G	VG	MG	G	M
	LTE-A Pro FD-MIMO Macro 5	G	VG	MG	VG	VG	G	MG
Disaster-aware Information Gathering (DIG)	LTE-A Pro FD-MIMO Macro 1	G	G	MG	G	VG	MG	VG
	LTE-A Pro FD-MIMO Macro 2	G	VG	MG	VG	MG	G	G
	LTE-A Pro FD-MIMO Macro 3	MG	G	MG	G	G	VG	VG
	LTE-A Pro FD-MIMO Macro 4	VG	AG	VG	AG	VG	VG	G
	LTE-A Pro FD-MIMO Macro 5	AG	VG	VG	AG	AG	VG	G
Live Video Streaming for Emergency Manipulation (LVS-EM)	LTE-A Pro FD-MIMO Macro 1	VG	G	VG	G	G	MG	G
	LTE-A Pro FD-MIMO Macro 2	G	MG	M	AG	VG	G	MG
	LTE-A Pro FD-MIMO Macro 3	MG	G	G	MG	MG	G	VG
	LTE-A Pro FD-MIMO Macro 4	VG	AG	AG	AG	G	VG	M
	LTE-A Pro FD-MIMO Macro 5	AG	VG	VG	AG	VG	AG	MG
Image Transmission for Emergency Manipulation (IMT-EM)	LTE-A Pro FD-MIMO Macro 1	G	VG	G	VG	MG	G	VG
	LTE-A Pro FD-MIMO Macro 2	VG	G	G	VG	G	M	VG
	LTE-A Pro FD-MIMO Macro 3	G	M	MG	G	VG	MG	G
	LTE-A Pro FD-MIMO Macro 5	AG	VG	AG	VG	AG	VG	M
	LTE-A Pro FD-MIMO Macro 4	AG	VG	VG	AG	AG	G	MP

TABLE III
THE SIMULATED DRONES.

Drone	Services	Disaster Severity Level
1	IMT, 3DS	Low
2	IMT, DIG, LVS-EM	Elevated
3	LVS-EM	Guarded
4	IMT-EM	Elevated
5	IMT	Low
6	3DS, LVS-EM	High
7	LVS, 3DS, DIG	Severe
8	LVS	Low
9	DIG, IMT-EM	Guarded
10	3DS, IMT-EM	High

Considering the relative importance $\tilde{\omega}_{\tilde{p}s}$ of each service and the criteria weights w_e for both DM and nDM services, the final criteria weights are estimated for each drone with respect to the DSL encountered in each case, as well as to the services that each drone uses (figure 5).

Ranking of the networks alternatives is performed from

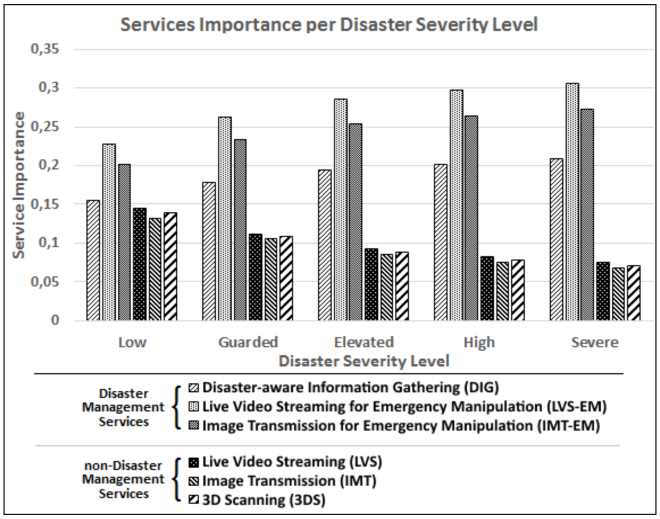

Fig. 2. The importance of each service per disaster severity level.

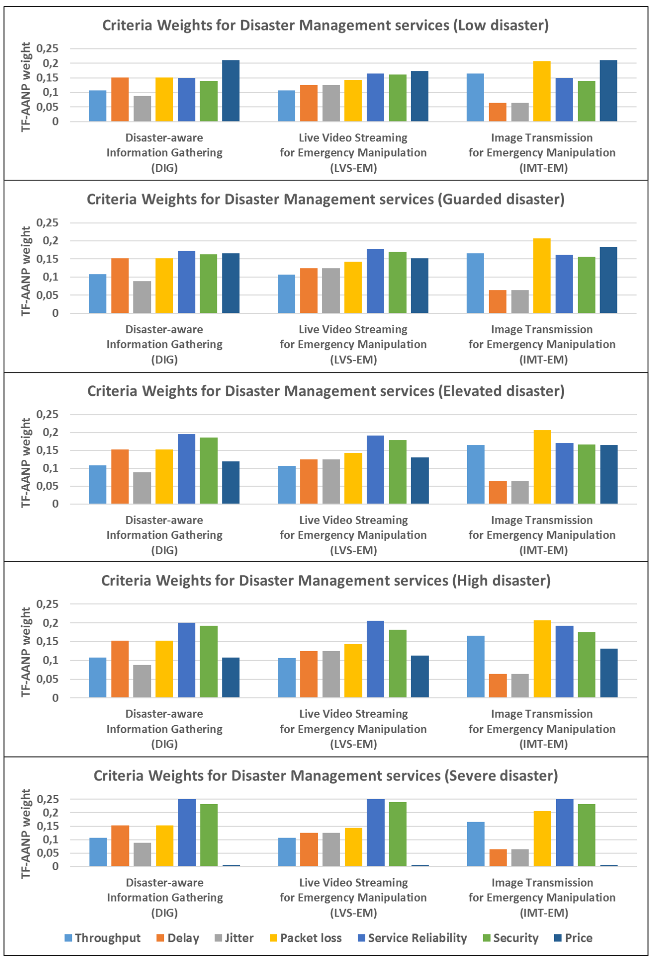

Fig. 3. The TF-AANP criteria weights for Disaster Management services per Disaster Severity Level.

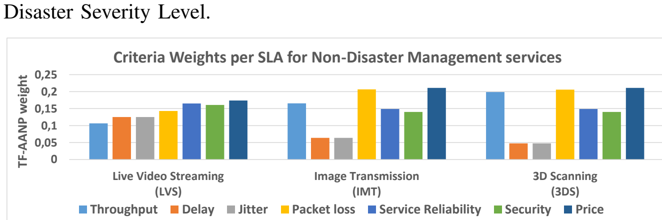

Fig. 4. The TF-AANP criteria weights for Non-Disaster Management services.

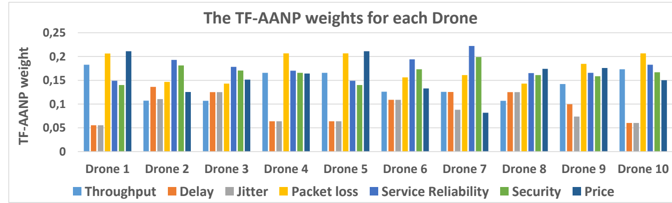

Fig. 5. The TF-AANP weights for each drone.

the DTFT-ACW algorithm using the aforementioned criteria weights for each drone.

Subsequently, the experimental results of the DTFT-ACW method are compared with the ones obtained from the TFT [17], the DTOPSIS [18], the FSAW [20] and the FMEW [21] algorithms (Table IV). When the DSL is Low (drone 1, 5 and 8) or Guarded (drones 3 and 9) the results of the DTFT-ACW, the TFT and the DTOPSIS are quite similar, due to the similar relative importance considered from the DTFT-ACW for each service. In these cases, the FSAW and the FMEW algorithms also accomplish satisfactory results. However, when the DSL gets worse, the DTFT-ACW assigns higher importance to DM services and selects the most appropriate network to satisfy their strict constraints. Indicatively, in the case of vehicle 7 where DSL becomes Severe, the DTFT-ACW selects the LTE-A Pro FD-MIMO Macro 5 network, which provides AG for throughput, packet loss and service reliability, as well as VG for delay, jitter and security, for the DIG disaster management service. On the contrary, the results of both TFT, DTOPSIS, FSAW and FMEW are negatively affected from the existence of nDM services in the vehicle 7 ignoring the Severe level of the occurred natural disaster. Specifically, the TFT, FSAW and FMEW select the LTE-A Pro FD-MIMO Macro 1 network, which provides worse specifications for the DIG service (e.g. VG for service reliability, G for throughput, delay and packet loss, as well as MG for jitter and security). Accordingly, the DTOPSIS selects the LTE-A Pro FD-MIMO Macro 3 network, which also provides worse specifications for the aforementioned disaster management service (e.g. MG for throughput and jitter, as well as G for delay, packet loss and service reliability).

Regarding the computational complexity, the DTFT-ACW and DTOPSIS succeed the most efficient results. Specifically, in both algorithms, during the first run the network selection process introduces a $O(n^2)$ complexity, due to the weighting and normalization of $n \times m$ decision matrices. Subsequently, for each next run where $AL(t) = AL(t_{prev})$, constant time is required for the completion of the network selection by performing simple checks to the results obtained during the t_{prev} time, resulting in $O(n)$ complexity. On the contrary, the TFT, FSAW and FMEW algorithms always result in $O(n^2)$ complexity, since they manipulate $n \times m$ decision matrices, each time they perform the network selection.

TABLE IV
NETWORKS' CLASSIFICATION IN RESPECT OF DTFT-ACW, TFT, DTOPSIS, FSAW AND FMEW RESULTS.

Method / Networks	Drone 1					Drone 2					Drone 3					Drone 4					Drone 5				
	DTFT-ACW	TFT	DTOPSIS	FSAW	FMEW	DTFT-ACW	TFT	DTOPSIS	FSAW	FMEW	DTFT-ACW	TFT	DTOPSIS	FSAW	FMEW	DTFT-ACW	TFT	DTOPSIS	FSAW	FMEW	DTFT-ACW	TFT	DTOPSIS	FSAW	FMEW
LTE-A Pro FD-MIMO Macro 1	**1**	**1**	**1**	2	**1**	3	2	**1**	2	4	3	3	3	2	3	3	3	4	3	4	**1**	**1**	**1**	2	**1**
LTE-A Pro FD-MIMO Macro 2	2	2	2	**1**	3	4	4	4	4	3	4	4	4	5	5	4	4	3	4	3	2	2	2	**1**	3
LTE-A Pro FD-MIMO Macro 3	3	3	5	3	2	5	5	5	5	5	5	5	5	4	4	5	5	5	5	5	3	3	5	3	2
LTE-A Pro FD-MIMO Macro 4	5	5	3	5	4	2	**1**	3	**1**	**1**	2	2	2	**1**	**1**	**1**	**1**	**1**	**1**	**1**	4	4	3	5	4
LTE-A Pro FD-MIMO Macro 5	4	4	4	4	5	**1**	3	2	3	2	**1**	**1**	**1**	3	2	2	2	2	2	2	5	5	4	4	5

Method / Networks	Drone 6					Drone 7					Drone 8					Drone 9					Drone 10				
	DTFT-ACW	TFT	DTOPSIS	FSAW	FMEW	DTFT-ACW	TFT	DTOPSIS	FSAW	FMEW	DTFT-ACW	TFT	DTOPSIS	FSAW	FMEW	DTFT-ACW	TFT	DTOPSIS	FSAW	FMEW	DTFT-ACW	TFT	DTOPSIS	FSAW	FMEW
LTE-A Pro FD-MIMO Macro 1	3	**1**	**1**	2	2	4	**1**	2	**1**	**1**	3	3	4	**1**	**1**	3	2	3	4	4	3	**1**	2	**1**	**1**
LTE-A Pro FD-MIMO Macro 2	4	3	3	5	5	5	3	3	5	4	2	2	**1**	2	3	4	3	4	3	3	4	2	**1**	4	4
LTE-A Pro FD-MIMO Macro 3	5	5	4	4	4	3	2	**1**	3	2	**1**	**1**	2	3	2	5	4	5	5	5	5	5	5	5	5
LTE-A Pro FD-MIMO Macro 4	2	4	5	**1**	**1**	2	5	5	4	3	4	4	3	5	5	**1**	**1**	2	**1**	**1**	**1**	4	4	2	2
LTE-A Pro FD-MIMO Macro 5	**1**	2	2	3	3	**1**	4	4	2	5	5	5	5	4	4	2	2	**1**	2	2	2	3	3	3	3

IV. CONCLUSION

This paper proposes the DTFT-ACW network selection algorithm for supporting drone services through 5G network architectures. The discussed algorithm accomplishes the ranking of the candidate networks considering the relative importance of each service, as well as the weights of the selection criteria, obtained using the TF-AANP method. The severity level of an occurred natural disaster is considered, while the criteria used for network evaluation include throughput, delay, jitter, packet loss, service reliability, security and price. Performance evaluation showed that the DTFT-ACW algorithm outperforms existing network selection methods by satisfying the strict constraints of disaster management services, in situations where an occurred natural disaster becomes severe. Furthermore, the DTFT-ACW algorithm eliminates the computational complexity by considering past network selection decisions in cases where the list of available access networks has not been changed.

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