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Energy and Delay Aware Task Assignment Mechanism for UAV-based IoT Platform

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Abstract—**Unmanned Aerial Vehicles (UAVs) are gaining much momentum due to the vast number of their applications. In addition to their original missions, UAVs can be used simultaneously for offering Value Added Internet of Things Services (VAIoTS) from the sky. VAIoTS can be achieved by equipping UAVs with suitable IoT payloads and organizing UAVs' flights using a central System Orchestrator (SO). SO holds the complete information about UAVs, such as their current positions, their amount of energy, their intended use-cases or flight missions, and their onboard IoT device(s). To ensure efficient VAIoTSs, there is a need for developing a smart mechanism that would be executed at the SO in order to take into account two major factors: *i*) the UAVs' energy consumption and *ii*) the UAVs' operation time. To effectively implement this mechanism, this paper presents three complementary solutions, named Energy Aware UAV Selection (EAUS), Delay Aware UAV Selection (DAUS), and Fair Trade-off UAV Selection (FTUS), respectively. These solutions use Linear Integer Problem (LIP) optimizations. While the EAUS solution aims to reduce the energy consumption of UAVs, the DAUS solution aims to reduce the operational time of UAVs. Meanwhile, FTUS uses a bargaining game to ensure a fair trade-off between the energy consumption and the operation time. The results obtained from the performance evaluations demonstrate the efficiency and the robustness of the proposed schemes. Each solution demonstrates its efficiency at achieving its planned goals.**

Index Terms—**Drone, Unmanned Aerial Vehicle (UAV), Unmanned Aerial System (UAS), Internet of Things (IoT), UAV Selection Mechanism, System Orchestrator, Linear Integer Problem (LIP), and Game Theory.**

I. Introduction

Recently, the use of UAVs has been widely deployed in civilian sectors [1] [2], such as public safety, environmental monitoring, sea and ocean industry, boarder control, and parcel delivery [3]. The diversity and the increase in UAV use-cases have paved the way for new businesses to appear. According to the European Drones Outlook Study [4], the UAV's market, with their diverse applications, shows an increase of EUR 10 billion annually by 2035 and over EUR 15 billion annually by 2050. For instance, while UAVs are performing their original tasks, they can simultaneously be used as an IoT platform to provide VAIoTSs [5]. Indeed, a user may be interested in measuring the degree of air pollution in a certain region, while the mail delivery UAV of the post office is flying above that area. Therefore, the mail delivery UAV can also measure the air pollution (in addition to its original task) without affecting its primary responsibility [1].

To benefit from VAIoTS, there is a need to have a robust System Orchestrator (SO) [3], [6] to organize the UAVs flights and manage the IoT tasks requested by the users. It is assumed that the airspace of the UAV flights is partitioned into different zones, where each airspace zone is exclusively managed by one SO. In addition, the airspace partitioning and the management of SOs are conducted under the authorities of different countries' aviation administrations. The example of airspace partitioning is the air route traffic control centers that are planned and performing under the authority of the United States Federal Aviation Administration.

In the envisioned system, each SO holds the complete and updated information about the current status of UAVs, their routes, their battery conditions, and their equipment. In addition, using efficient mechanisms, e.g. collision avoidance methods [7], SO manages optimal UAV flights in unmanned air space considering the best flight way-points. The SO is also designed to command-and-control IoT payloads on board UAVs whenever needed in the area of interest. It also employs any possible communication technology, e.g. LTE 4G/5G networks to connect with the UAVs [8], [9]. In fact, SO is designed to handle any incoming event, i.e. IoT task requested by the users of the service. In fact, to handle an event, the SO uses the information about the geographical locations of the UAVs, their available energy, and their onboard IoT devices (Fig. 3). Thus, having these information and employing efficient mechanisms, the SO will be able to select the most appropriate UAVs which are present in the UAV network to handle a specific event requested by a client.

Furthermore, when a task is assigned to a UAV, it is necessary for the UAV to reach to the right place at the right time. In fact, due to clock drifts, the timing of electronic devices onboard a UAV may differ. Moreover, based on [10], at high speed of UAVs, the time synchronization errors may affect the temporal accuracy of the measurement timestamps. Thus, to obtain tempo-

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ral accuracy for the IoT tasks (for example sensing or video streaming), SO shall update and synchronize the UAVs clocks frequently, e.g. at each task assignment and per completing the task. Moreover, at each task, when assigning a task to a set of UAVs, the SO shall also make a relative time synchronization of the UAVs.

To benefit from the advantages of VAIoTS, in this paper, we present an efficient UAV selection mechanism to be employed by the SO. Actually, to select UAVs, our mechanism uses the information about the UAVs geographical positions, their onboard IoT payloads, their energy budget, the priority level of the events, and the required time to handle the events. Furthermore, our proposed UAV selection mechanism is designed based on three optimization solutions: the UAVs energy consumption, the UAVs operation time, and a fair trade-off solution when considering both the energy and the time. In the UAVs energy consumption [11]–[13], the three sources considered include: i) the energy needed for UAV's traveling; ii) the energy needed for performing an IoT task (e.g. sensing or video streaming); and iii) the energy needed for UAV's data transmission. In addition, another source of energy consumption pertains to the UAVs Global Positioning System (GPS). Based on [14] [15], the energy consumed for getting GPS information is constant. In this paper, we assume that the energy needed for GPS is already included in the energy needed for the UAVs traveling. Similar to the UAV's energy consumption, for the UAV's operation time, we consider the times required for traveling, handling an event, and data transmission.

A primary version of the UAV selection mechanism for handling the IoT tasks was proposed in [1]. The mechanism proposed therein uses a primitive model for the problem formulation. It also takes into account only one IoT event at a given time to be handled by UAVs. In contrast to the mechanism proposed in [1], for the system modeling, in this paper we take into account the environmental effects on UAVs' flights and performance. These effects are acknowledged by considering the impact of wind on UAVs' speeds; the effect of temperature on the IoT devices; and the effect of path-loss and shadowing on UAVs' data transmissions. In addition, in this paper, we propose a new mechanism that considers multiple events at the same time with variant priority levels, wherein the priorities between IoT events to be carried out by UAVs and new incoming IoT events are considered. The reason for this consideration is that some new IoT events may need to be handled urgently. Moreover, to handle the IoT tasks, in this paper, the mechanism is defined based on four steps, each one with a specific functionality. Furthermore, in this paper, we propose a third optimization that aims at finding a fair trade-off solution between the two conflicting objectives, i.e. the UAVs' energy consumption and their operation time. In addition, in our analysis, we evaluate the performance of the optimization solutions by varying the number of UAVs, increasing the size of flying area,

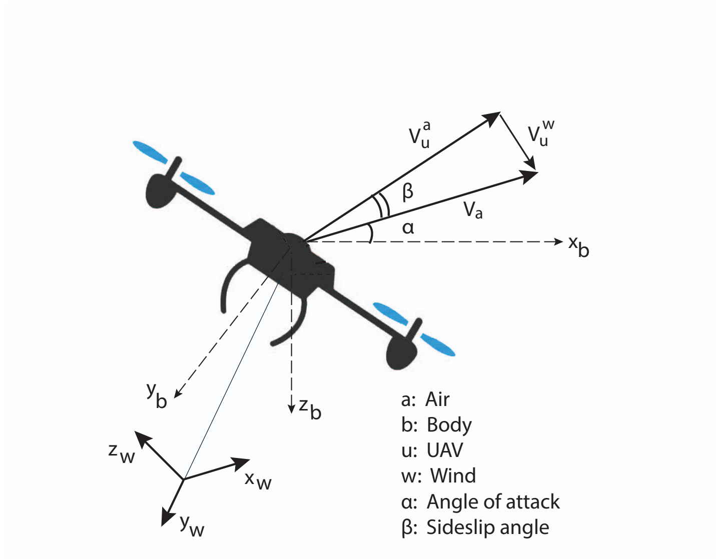

Figure 1. *A*ir-relative velocity and applied wind for a UAV.

varying the number of events, and increasing the types of IoT devices onboard UAVs and required by the events.

The remainder of this paper is organized as follows. In Section II, we introduce the model and formulate the problem. In Section III, we present our envisioned UAV selection mechanisms. Section IV explains the selection of eligible UAVs for performing different events. The performance evaluation is conducted in Section V, and eventually, the paper concludes in Section VI.

II. System model and problem formulation

In this section, we formulate the energy consumption and the operation time required for a rotary UAV when selected to perform an IoT task. In the modeling, we consider the energy and the time required for: i) the traveling, ii) the sensing and processing, and iii) the data transmission. In the model, $\mathcal{N}$ means the set of UAVs in the network and $\mathcal{E}$ stands for an event.

A. Effect of wind on UAVs energy consumption

In this subsection, we evaluate the effect of wind on a UAV's velocity to consider a reasonable energy consumption model for UAVs. In reality, wind effects result from the UAV's body b and surrounding air a interactions and depends on wind vector w. Let V_u^a be the air relative velocity vector of a UAV u and V_a be the magnitude of V_u^a. In addition, the direction of the wind w is characterized by direction of V_u^a with respect to the body b. The wind direction is also specified by the side-slip angle α and the angle of attack β (Fig.1). The angle α is the angle between the velocity vector V_a and the longitudinal axis x_b and the angle β defines the longitudinal stability of the UAV u.

Based on [16], the transformation from the UAV's body frame b to the wind frame w is achieved using the sequence of UAV rotations, defined by $(R_1(0), R_2(\alpha), and R_3(-\beta))$:

$$R_1(0) = 1,\ R_2(\alpha) = \begin{bmatrix} \cos\alpha & 0 & -\sin\alpha \\ 0 & 1 & 0 \\ \sin\alpha & 0 & \cos\alpha \end{bmatrix},$$

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$$\text{and } R_3(-\beta) = \begin{bmatrix} \cos\beta & -\sin\beta & 0 \\ \sin\beta & \cos\beta & 0 \\ 0 & 0 & 1 \end{bmatrix}, \tag{1}$$

Meanwhile, the rotation matrix is calculated by:

$$R_b^w = R_1(0)R_2(\alpha)R_3(-\beta)$$

$$= \begin{bmatrix} \cos\alpha\cos\beta & -\cos\alpha\sin\beta & -\sin\alpha \\ \sin\beta & \cos\beta & 0 \\ \sin\alpha\cos\beta & -\sin\alpha\sin\beta & \cos\alpha \end{bmatrix}, \tag{2}$$

Let $V_u^w = \begin{bmatrix} V_a & 0 & 0 \end{bmatrix}^T$ denote the inertial velocity vector that is measured in the direction of the wind axis. Using the components u, v, and w, the velocity vector of UAV relative to surrounding air can be defined as: $V_u^a = \begin{bmatrix} u & v & w \end{bmatrix}^T$, where $(V_u^a = R_w^b \; V_u^w)$. Using Equation (2), we have:

$$\begin{bmatrix} u \\ v \\ w \end{bmatrix} = \begin{bmatrix} \cos\alpha\cos\beta & -\cos\alpha\sin\beta & -\sin\alpha \\ \sin\beta & \cos\beta & 0 \\ \sin\alpha\cos\beta & -\sin\alpha\sin\beta & \cos\alpha \end{bmatrix} \begin{bmatrix} V_a \\ 0 \\ 0 \end{bmatrix}, \tag{3}$$

Thus, we obtain the following airspeed components for V_u^a:

$$\begin{bmatrix} u & v & w \end{bmatrix}^T = V_a \begin{bmatrix} \cos\alpha\cos\beta & \sin\beta & \sin\alpha\cos\beta \end{bmatrix}^T, \tag{4}$$

Thus, we can compute the airspeed V_a, and the angles α and β as follows:

$$V_a = \sqrt{u^2 + v^2 + w^2}, \tag{5}$$

$$\alpha = \arctan(\frac{w}{u}), \tag{6}$$

$$\beta = \arcsin(\frac{v}{V_a}), \tag{7}$$

Let $u \in \mathcal{N}$ be a UAV in $\mathcal{N}$. Let $\mathcal{D}_{u,\mathcal{E}}$ be the distance from the UAV u to the event $\mathcal{E}$. To calculate the distance $\mathcal{D}_{u,\mathcal{E}}$, we use the Euclidean three-space formulation:

$$\mathcal{D}_{u,\mathcal{E}} = \sqrt{(x_\mathcal{E} - x_u)^2 + (y_\mathcal{E} - y_u)^2 + (z_\mathcal{E} - z_u)^2}, \tag{8}$$

Furthermore, to compute the traveling time Υ_u^{Travel} from the location of the UAV u to the event location $\mathcal{E}$, we use the following relation:

$$\Upsilon_u^{Travel} = \frac{\mathcal{D}_{u,\mathcal{E}}}{V_a}, \tag{9}$$

In the literature, different studies use linear relations to compute the energy consumption of the UAVs [17]–[19]. In our study, we consider the relation defined in [20] to compute the energy consumption for traveling ξ_u^{Travel} of a rotary wing UAV u to travel between two locations by:

$$\xi_u^{Travel} = \Upsilon_u^{Travel} \cdot (P_V + P_H), \tag{10}$$

where, P_V is the power consumption for the vertical movement and P_H is the power consumption for the horizontal movement.

B. Energy consumption of UAV's onboard IoT devices

During UAV flights, the continuous use of IoT devices onboard will severely consume the energy resources of the UAV and will exhaust the UAV's batteries. Therefore, it is mandatory to remotely turn on-and-off the on-board sensors or cameras at the right time and in the right place. In fact, to enhance the UAV's energy efficiency, onboard IoT devices should be actuated only when UAVs fly above the intended areas at particular times of interest. Furthermore, the UAVs may fly in the environments with cold or hot temperature, e.g. in hot desert or above volcano. Consequently, the power consumption by IoT devices when crossing from these environments is affected. Therefore, considering the effect of temperature on CPU of IoT devices onboard UAV, based on [21], the total CPU power consumption P_{CPU} for each IoT device per UAV can be calculated by:

$$P_{CPU} = \sum_{i=0}^{n} (P_{leak} + P_{charge} + P_{short}), \tag{11}$$

where P_{leak} denotes the leakage power, P_{charge} denotes the power for charging the capacitors, and P_{short} denotes the short-circuit power. According to [22], P_{charge} is formulated as:

$$P_{charge} = \mu \cdot C \cdot f \cdot V^2, \tag{12}$$

where μ is a constant number which presents the system's active and switching modes. In addition, C denotes capacitance, V denotes the voltage swing across C, and f refers to the switching frequency. Formally, P_{short} is defined by:

$$P_{short} = (\eta - 1) \cdot P_{charge}, \tag{13}$$

where η denotes the scaling factor and demonstrates the effects of short-circuit power. Based on [23], P_{leak} originates from the leakage current I_{leak}, and is calculated by:

$$P_{leak} = I_{leak} \cdot V_{dd}, \tag{14}$$

C. Communication modeling

In this sub-section, we model the communications between a UAV u and an eNodeB $\mathcal{B}$. In our model, we use an automatic repeat request (ARQ) scheme for data transmissions to increase the communication reliability. The ARQ scheme transmits a packet until it successfully arrives at the destination address. That means a maximum number of retransmissions M, while M varies randomly according to the channel conditions. For the communication, we use a combined path loss and shadowing model while neglecting the effect of interference. In addition, for radio propagation of the UAV's transmitter, we consider the case of typical urban environment and the optimal UAV altitude. In combined path loss and shadowing model, based on [24], the ratio of received to transmitted power in (dB) is defined by:

$$\frac{P_r}{P_t}(dB) = 10\log_{10} K - 10\varphi \log_{10} \frac{\mathcal{D}_{u,\mathcal{B}}}{\mathcal{D}_0} + n_{dB}, \tag{15}$$

where P_r and P_t denote the received and transmitted powers at the UAV u, K is the path loss coefficient (a

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unitless constant), φ is the path loss exponent, $\mathcal{D}_{u,\mathcal{B}}$ denotes the distance between the transmitter u and receiver $\mathcal{B}$, $\mathcal{D}_0$ denotes the reference distance, and $n_{\mathcal{B}}$ denotes a Gaussian distributed random variable with zero-mean and variance $\sigma^2_{\psi_{dB}}$.

In UAV communications an important concern pertains to the probability of outage. When a UAV ($u \in \mathcal{N}$) fails to transmit its packet to an eNodeB $\mathcal{B}$, the link ($u-\mathcal{B}$) is in outage. This happens if P_r falls below minimum received power threshold γ_{th}. In fact, the received power P_r at any distance $\mathcal{D}_{u,\mathcal{B}}$ from the transmitter becomes a log-normal distribution with probabilities falling below γ_{th}, that is caused by path loss and shadowing. Thus, the outage probability is expressed as: $p_{out}(\gamma_{\text{th}}, \mathcal{D}_{u,\mathcal{B}}) = p(Pr(\mathcal{D}_{u,\mathcal{B}}) \leqslant \gamma_{\text{th}})$. In log-normal shadowing, $P_r(\mathcal{D}_{u,\mathcal{B}})$ and the Q function ($Q_{(z)} = \frac{1}{\sqrt{2\pi}} \int_z^x exp(-\frac{x^2}{2})\ d_x$) are used to determine the probability that the received signal falls below a particular level. Note that $Q_{(z)} = 1 - Q_{(-z)}$. In addition, the outage probability is calculated by the cumulative density function as [25]:

$$p\Big(P_r(\mathcal{D}_{u,\mathcal{B}}) \leqslant \gamma_{\text{th}}\Big) = Q(\frac{P_r - \gamma_{\text{th}}}{\sigma_{\psi_{dB}}}) = 1 - Q(\frac{\gamma_{\text{th}} - P_r}{\sigma_{\psi_{dB}}}), \qquad (16)$$

Meanwhile, using Equation 15 for the average combined path loss and shadowing, we have $P_r = P_t + 10\log_{10} K - 10\varphi \log_{10} \frac{\mathcal{D}_{u,\mathcal{B}}}{\mathcal{D}_0}$. Therefore, the outage probability ($\mathcal{P}_{u,\mathcal{B}}$) between u and $\mathcal{B}$ will be [24]:

$$\begin{aligned}\mathcal{P}_{u,\mathcal{B}} &= p\Big(P_r(\mathcal{D}_{u,\mathcal{B}}) \leqslant \gamma_{\text{th}}\Big), \\ &= 1 - Q\Big(\frac{\gamma_{\text{th}} - (P_t + 10\log_{10} K - 10\varphi\log_{10} \frac{\mathcal{D}_{u,\mathcal{B}}}{\mathcal{D}_0})}{\sigma_{\psi_{dB}}}\Big), \qquad (17)\end{aligned}$$

where V_{dd} denotes the supply voltage of the circuit. Basically, the UAV's energy consumption by the IoT devices when they are in active mode is calculated by:

$$\xi_u^{SenseProcess} = P_{CPU} \cdot \Delta_t, \qquad (18)$$

where Δ_t refers to the duration that the IoT device is active and $\xi_u^{SenseProcess}$ refers to the energy consumption of sensing-and-processing of the IoT device.

1) Communication time modeling: An IoT gateway employed on board a UAV is assumed to use buffering system for handling data packets $\mathcal{K}$ for the transmission. These packets contain the data of sensed information from an event $\mathcal{E}$. Actually, this sub-section is developed to evaluate the average transmission time $\Upsilon_u^{Transmit}$ of sensed data from the UAV u to an eNodeB $\mathcal{B}$. Let $T_u^{Transmit}$ be the sojourn time of a packet before its transmission to $\mathcal{B}$. Thus, the average transmission time can be calculated by:

$$\Upsilon_u^{Transmit} = \mathcal{K} \cdot T_u^{Transmit}, \qquad (19)$$

As a matter of fact, a successful reception of a packet at eNodeB $\mathcal{B}$ requires a random number of packet retransmissions. To investigate the delay time in accordance with the retransmission events, there is a need to measure the average sojourn time $T_u^{Transmit}$ of a packet in the buffer of the transmitter u. It is worth noting that, the average sojourn time $T_u^{Transmit}$ of a packet is the average time elapsed from the starting of it's transmission until the successful reception at the receiver. Based on Pollaczek-Khinchin equation [26], the packet's sojourn time in the buffer is calculated by:

$$T_u^{Transmit} = \mathbb{E}(N_{u,\mathcal{B}}) T_F, \qquad (20)$$

where T_F denotes the required time for a single transmission of a packet and $\mathbb{E}(N_{u,\mathcal{B}})$ denotes the average number of retransmissions of the packets transmitted from u. As we explained earlier, in an ARQ scheme, until a successful reception at the eNodeB $\mathcal{B}$, the maximum number of retransmissions M of a single packet is conducted. Let us consider that a packet will be discarded, if it fails to be received after M retransmissions. In addition, the number of retransmissions $N_{u,\mathcal{B}}$ between the transmitter u and the receiver $\mathcal{B}$ alters randomly according to the UAV's location and the channel conditions. Based on [27], the average number of retransmissions $\mathbb{E}(N_{u,\mathcal{B}})$ is calculated by:

Table I
Summary of Notations.

Notation	Description
u	UAV
$\mathcal{B}$	eNodeB
V_u^a	UAV's air relative velocity
V_a	UAV's air speed
R_b^w	UAV's turning radius (rotation)
λ	energy consumption per meter
$\mathcal{D}_{u,\mathcal{E}}$	distance from the UAV to the event $\mathcal{E}$
$\Upsilon_u^{Endurance}$	maximum flight time of a UAV u
μ	system's switching mode (constant)
C	capacitance
V	voltage swing across C
f	switching frequency
η	scaling factor (effects of short-circuit power)
Δ_t	device on-and-off time
V_{dd}	supply voltage of circuit
M	maximum number of retransmissions
φ	path loss exponent
K	path loss coefficient
$\mathcal{D}_{u,\mathcal{B}}$	distance between u and $\mathcal{B}$
$\mathcal{D}_0$	reference distance (typically one meter)
γ_{th}	target minimum received power level
$\mathcal{P}_{u,\mathcal{B}}$	outage probability
$\mathcal{K}$	number of data packets
T_F	time for a single packet transmission
$\mathbb{E}(N_{u,\mathcal{B}})$	average number of retransmissions
$\bar{P}$	average consumed power
P_u	power consumed per retransmission at UAV u
$m\mathcal{H}_u$	maximum altitude for a UAV
$\mathcal{E}$	an event
$\mathcal{E}_\Gamma$	a scheduled event
L	priority level of an event
$\mathcal{N}$	a set of eligible UAVs could be selected for a task
$\mathcal{S}_\mathcal{E}$	a set of devices required to handle an event
$\mathcal{S}_u$	a set of devices onborad a UAV u
Υ_{th}	threshold time
ξ_{th}	threshold energy
$\Upsilon_{u,\mathcal{E}}^{ToT}$	total time needed for handling an event $\mathcal{E}$
$\xi_{u,\mathcal{E}}^{ToT}$	total energy needed for handling an event $\mathcal{E}$

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$$\begin{aligned}\mathbb{E}(N_{u,\mathcal{B}}) &= 1+\sum_{m=1}^{M-1} P(F^1,...,F^m) = 1+\sum_{m=1}^{M-1}(\mathcal{P}_{u,\mathcal{B}})^m \\ &= \sum_{m=0}^{M-1}(\mathcal{P}_{u,\mathcal{B}})^m = \frac{1-\left(\mathcal{P}_{u,\mathcal{B}}\right)^M}{1-\mathcal{P}_{u,\mathcal{B}}}, \end{aligned} \tag{21}$$

where $P(F^1,...,F^m)$ describes the probability of a reception failure at the $1^{st},\ldots,m^{th}$ retransmissions. Considering that the channel realizations at every transmission are independent and identically distributed, the events of reception failures at every step are independent and hold equal probabilities, then $P(F^1,...,F^m) = (\mathcal{P}_{u,\mathcal{B}})^m$. Therefore, using Equations 20 and 21 results in:

$$\Upsilon_u^{Transmit} = \mathcal{K}\cdot T_F \cdot \mathbb{E}(N_{u,\mathcal{B}}) = \mathcal{K}\cdot T_F \cdot \frac{1-\left(\mathcal{P}_{u,\mathcal{B}}\right)^M}{1-\mathcal{P}_{u,\mathcal{B}}}. \tag{22}$$

2) Energy consumption model in communication: In this subsection, we evaluate the energy consumption ($\xi_u^{Transmit}$) required for the packet transmissions at UAV u. Let us consider a UAV u obtains a number of packets $\mathcal{K}$ for transmission in which these packets are the sensed data from an event $\mathcal{E}$. In fact, the number of packet retransmissions varies according to the channel characteristics and conditions. These variations in packet transmissions cause the power consumptions to be presented as random variables. Therefore, in this subsection we investigate the average power consumption ($\bar{P}$) and the average energy consumption $\xi_u^{Transmit}$ for the $\mathcal{K}$ packets data transmission. The average consumed power $\bar{P}$ in an ARQ scheme is computed by:

$$\begin{aligned}\bar{P} &= P_u \cdot P(S^1) + 2P_u\cdot P(F^1,S^2)+... \\ &+(M-1)P_u\cdot P(F^1,...,S^{M-1}) + MP_x\cdot P(F^1,...,F^{M-1}) \\ &= P_u\cdot\left(1+\sum_{m=1}^{M-1}P(F^1,...,F^m)\right) = P_u\cdot\left(1+\sum_{m=1}^{M-1}(\mathcal{P}_{u,\mathcal{B}})^m\right) \\ &= P_u\cdot\mathbb{E}(T_{u,\mathcal{B}}) = P_u\cdot\frac{1-\left(\mathcal{P}_{u,\mathcal{B}}\right)^M}{1-\mathcal{P}_{u,\mathcal{B}}}, \end{aligned}\tag{23}$$

where P_u denotes the power consumption for each retransmission by a UAV. $P(S^1)$ is the probability of successful reception at $\mathcal{B}$ of first transmission. $P(F^1,...,S^{M-1})$ is the probability of a reception failure in the 1^{st}, 2^{nd}, ..., $(M-2)^{th}$ retransmissions and a successful reception at the $(M-1)^{th}$ retransmission. A probability of an event $P(S^1)$ means that a packet is successfully received after the first transmission and the power consumption is equal to P_u. Subsequently, a probability of an event $P(F^1,S^2)$ means that a packet is received correctly after two retransmissions and the power consumption for this event equals to $2P_u$. Accordingly, a probability of the event $P(F^1,...,F^{M-1})$ explains that the 1^{st}, ...,$(M-1)^{th}$ retransmissions have failed and the power consumption will be equal to MP_u. Thus, the average power consumption is obtained by summing the possible values of power consumption and weighting their relevant probability of occurrence. The result in Equation (23) explains that the average power consumption can be explained by the product of the power for each retransmission P_u and the average number of retransmissions $\mathbb{E}(T_{u,\mathcal{B}})$. The average energy consumption $\Phi_{u,\mathcal{B}}$ of a single packet transmission is expressed as:

$$\begin{aligned}\Phi_{u,\mathcal{B}} &= P_u\cdot T_F\cdot P(S^1) + 2P_u\cdot T_F\cdot P(F^1,S^2)+...+(M-1)P_u \\ &\cdot T_F\cdot P(F^1,...,S^{M-1}) + MP_u\cdot T_F\cdot P(F^1,...,F^{M-1}) \\ &= P_u\cdot T_F\cdot\left(1+\sum_{m=1}^{M-1}(\mathcal{P}_{u,\mathcal{B}})^m\right) = P_u\cdot T_F\cdot\mathbb{E}(T_{u,\mathcal{B}}) = \bar{P}\cdot T_F, \end{aligned}\tag{24}$$

Therefore, the average energy consumption $\xi_u^{Transmit}$ to transmit the whole data packets ($\mathcal{K}$) can be obtained as:

$$\xi_u^{Transmit} = \mathcal{K}\cdot\Phi_{u,\mathcal{B}} = \mathcal{K}\cdot\bar{P}\cdot T_F. \tag{25}$$

III. Proposed solutions for UAV selection

Fig.3 shows a SO-based selection mechanism that works by selecting the appropriate UAVs to handle variant IoT events. Let $\mathcal{E}$ be the incoming IoT events (the events that have recently happened in the UAV network) and let $\mathcal{E}_\Gamma$ be the events scheduled by the selection mechanism. The scheduled events are the events that have been already assigned to UAVs. In the UAV selection process, the SO should consider event-based and UAV-based constraints. The SO must take into account the priority level of different events, the type(s) of IoT devices needed to handle the events, and the location of the events. The SO must also select the most appropriate UAVs for each event, taking into account the UAVs positions, the types of IoT devices mounted on UAVs, the UAVs remaining energy level, and the amount of IoT devices onboard UAVs. Actually, a UAV may be equipped with variant types of devices, such as cameras and different types of environmental sensors concurrently.

Considering these constraints, in this paper, the proposed selection mechanism happens in four steps (Fig. 2). In the first step, the events are assigned to the system and sorted based on their priority levels. In the second step, constraints and rules are applied for each event level. This is performed to select the eligible UAVs for performing the events of that level. In the third step, a subset of the eligible UAVs are selected to handle the sorted events. In this step, three optimization solutions are proposed: i) the first optimization aims at minimizing as much as possible the UAV's energy consumption regardless of UAV's operation time; ii) the second optimization aims at minimizing the UAV's operation time regardless of the UAV's energy consumption; and iii) the third optimization, using bargaining game, seeks a fair tradeoff between both the UAV's energy consumption and the UAV's operation time. In the fourth step, the scheduled events $\mathcal{E}_\Gamma$ are refined. For the sake of readability of the paper, in this section, we explain the first, second and the fourth steps while the third step, that includes the optimization problems, will be discussed in Section IV.

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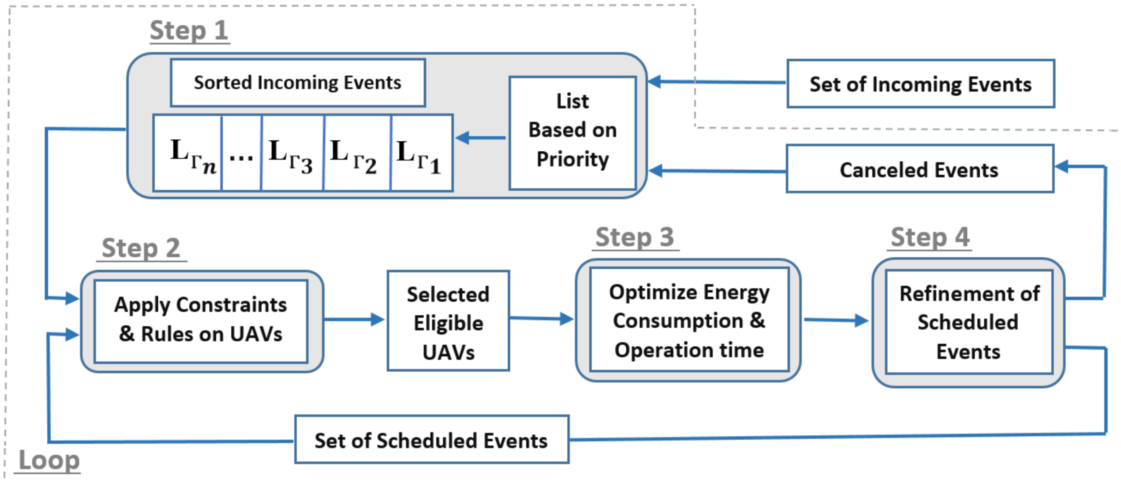

Figure 2. *The procedure of eligible UAV selection mechanism for handling incoming IoT events.*

A. First Step: Selection of eligible UAVs

The IoT services (i.e. the events that recently occurred) appealed by the UAV network users have priority levels. In fact, some events may need urgent handling than other events. For instance, video streaming from a fatal driving of a wicked person in a street has higher priority than taking a picture from a ceremony. Therefore, for UAV selection for different events, we assign a priority level for each event. We use the priority vector $L = \{L_1, L_2, L_3, \cdots, L_n\}$ to prioritize the service requests. In priority levels, the index of each priority refers to the priority level of the event. This is while the events with the higher priority levels are scheduled first. In addition, if multiple events obtain an equal priority level, then these events should be scheduled concurrently. Hence, the proposed mechanism groups and sorts the events based on their priority levels, where the events with highest priorities are handled first. Next, the grouped and sorted events are sent to the second step.

B. Second Step: Applying constraints and rules

To perform IoT operation for an event $\mathcal{E}$, let us consider $\mathcal{S}_{\mathcal{E}}$ be the set of IoT devices needed for the event and $\mathcal{S}_u$ be the set of IoT devices on-board a UAV u. Let $m\mathcal{H}_u$ be the maximum altitude where a UAV u is permitted to fly. Formally, for handling an event $\mathcal{E}$, a set of eligible UAVs ($\ddot{\mathcal{N}}$) should be selected with these constraints:

- **UAV selection constraint:** UAV u can handle an event or a set of events at a certain location at a given time. This means that a UAV cannot be at disparate locations simultaneously to handle different events. Formally, $\ddot{\mathcal{N}}_i \cap \ddot{\mathcal{N}}_j = \emptyset$, where $\ddot{\mathcal{N}}_i$ and $\ddot{\mathcal{N}}_j$ are the set of selected UAVs for handling the events i and j.
- **Device constraint:** The eligible UAVs $\ddot{\mathcal{N}}$ should obtain the prescribed IoT devices (s) for handling a scheduled event $\mathcal{E}$. Formally, $\mathcal{S}_{\mathcal{E}} \subseteq \bigcup_{u \in \ddot{\mathcal{N}}_{\mathcal{E}}} \mathcal{S}_u$, where $\ddot{\mathcal{N}}_{\mathcal{E}}$ is the set of UAVs that are selected to handle the event $\mathcal{E}$, $\mathcal{S}_{\mathcal{E}}$ is the set of devices needed for handling the event $\mathcal{E}$, and $\mathcal{S}_u$ is the set of IoT devices mounted on a UAV u.
- **Energy constraint:** For handling an event $\mathcal{E}$, the selected UAVs should contain adequate energy (battery) resources. Formally, $\xi_u^{Battery} > \xi_{u,e}^{ToT}$.
- **Time constraint:** To handle a scheduled event $\mathcal{E} \in \mathcal{E}_\Gamma$, the time latency of a selected UAV ($u \in \ddot{\mathcal{N}}$) should not outstrip the time threshold Υ_{th}.
- **Altitude constraint:** The selected UAV u should have the ability to fly at the altitude of the event $\mathcal{E}$. Formally, $m\mathcal{H}_u \geq Z_{\mathcal{E}}$, where $m\mathcal{H}_u$ denotes the the maximum altitude that a UAV flies and $Z_{\mathcal{E}}$ denotes the altitude of the event $\mathcal{E}$.

In addition to the constraints for UAV selection, a set of rules ($\mathcal{R}$) are also defined to select the eligible UAVs from the scheduled events. These rules $\mathcal{R}$ allows the designers of the selection mechanism to define the selection procedure for different use-cases. In the UAV selection, let us state that after applying the constraints and rules, if any UAV or a set of UAVs that are currently assigned to handle a scheduled event $\mathcal{E}_\Gamma$ are selected to handle a new event, then the event $\mathcal{E}_\Gamma$ should be stopped and postponed for the next rounds.

Example. In the following, we use an example to show how to apply a rule $\mathcal{R}$ for the UAV selection process. For an upcoming event, we add the following rule $\mathcal{R}$: $< \forall\ e_\Gamma \in \mathcal{E}_\Gamma, \forall u \in \ddot{\mathcal{N}}_{e_\Gamma} : L_{\mathcal{E}} > L_{\mathcal{E}_\Gamma}, \exists s \in \mathcal{S}_u \cap \mathcal{S}_{\mathcal{E}}, \mathcal{Q}_{e_\Gamma} < \mathcal{Q}_{th}, \xi_u^{Battery} > \xi_{u,e}^{ToT} \Rightarrow \text{Add u in } \ddot{\mathcal{N}} >$ where $\mathcal{Q}_{e_\Gamma}$ is the amount of accomplished task from a scheduled event e_Γ, and $\mathcal{Q}_{th}$ is the predefined threshold that should not be exceeded before canceling a scheduled event e_Γ.

Note that when a UAV $u \in \ddot{\mathcal{N}}_{e_\Gamma}$ of a scheduled event $e_\Gamma \in \mathcal{E}_\Gamma$ is selected to be used by another incoming event $\mathcal{E}$, then the scheduled event e_Γ should be canceled. In this example, a rule $\mathcal{R}$ is defined to allow any UAV $u \in \ddot{\mathcal{N}}_{e_\Gamma}$ that is scheduled for performing a scheduled event $e_\Gamma \in \mathcal{E}_\Gamma$ can be added as eligible UAV $\ddot{\mathcal{N}}$ for the incoming event $\mathcal{E}$ iff: *i*) the event $\mathcal{E}$ has higher priority than the ongoing event e_Γ; *ii*) the UAV u has the IoT devices that are needed by $\mathcal{E}$; *iii*) the amount of accomplished task $\mathcal{Q}_{e_\Gamma}$ from the event e_Γ should not outstrip $\mathcal{Q}_{th}$, this constraint is suitable for saving the energy budget of UAVs. Actually, a canceled event would be stopped and can be handled from scratch at a later time; *iv*) the residual energy at UAV u ($\xi_u^{Battery}$) should be more than the required energy to handle the incoming event $\mathcal{E}$ ($\xi_{u,e}^{ToT}$). As a matter of fact, the UAV's energy must be enough for handling the event $\mathcal{E}$.

For instance, if we update $\mathcal{R}$, by removing the constraint that has relation with the amount of task accomplishment ($\mathcal{Q}_{e_\Gamma} < \mathcal{Q}_{th}$), as follows: $< \forall\ e_\Gamma \in \mathcal{E}_\Gamma, \forall u \in \ddot{\mathcal{N}}_{e_\Gamma} : L_\mathcal{E} > L_{\mathcal{E}_\Gamma}, \exists s \in \mathcal{S}_u \cap \mathcal{S}_\mathcal{E}, \xi_u^{Battery} > \xi_{u,e}^{ToT} \Rightarrow$ Add u in $\ddot{\mathcal{N}} >$. In this case, any UAV $u \in \ddot{\mathcal{N}}_{e_\Gamma}$ of a scheduled event $e_\Gamma \in \mathcal{E}_\Gamma$ can be selected as an eligible UAV for the incoming event $\mathcal{E}$ iff all the aforementioned constraints hold except Constraint (*iii*) that should be omitted. Moreover, if we do not add the rule $\mathcal{R}$ to the system, then the eligible UAVs $\ddot{\mathcal{N}}$ of the incoming event $\mathcal{E}$ would be selected only from the free UAVs and the UAVs of already scheduled UAVs would be not considered. △

C. Fourth Step: Refinement of the scheduled event(s)

The fourth step is developed to refine the UAVs after selecting the subset of eligible UAVs. This step is performed to assign new tasks for the variant UAVs and stop their current scheduled events. Let $\mathcal{U}$ be the selected subset of eligible UAVs. Formally, $\mathcal{U} = \mathcal{U}_1 \cup \mathcal{U}_2$, where $\mathcal{U}_1$ denotes the set of UAVs without previous tasks, and $\mathcal{U}_2$ denotes the set of UAVs that are busy and already performing other scheduled events. In this step, the SO sends a notification to the selected UAVs $\mathcal{U}$ to handle their assigned events. Furthermore, the SO cancels the events that are under the assignments of variant UAVs $\mathcal{U}_2$. The canceled events are sorted again and wait in the queue of incoming events to be executed in a later time.

IV. Optimal Solutions for UAV Selection

This section is developed to propose three solutions for selecting a subset of eligible UAVs to perform operations for various incoming IoT tasks. Employing these solutions, UAVs would carry out different IoT tasks for the incoming events $\mathcal{E}_L$ of a specific level L. These solutions are three Integer Linear Problem optimizations: *i*) the first optimization is developed to minimize as much as possible the energy consumption to carry out the events, *ii*) the second optimization is designed to minimize the time to perform UAVs IoT tasks without considering the UAVs energy consumption, and *iii*) the third solution is planned for finding a fair trade-off between the UAVs energy consumption and their operation time as the two conflicting objectives of the UAV selection mechanism. Let $\xi_{u,\mathcal{E}}^{ToT}$ and $\Upsilon_{u,\mathcal{E}}^{ToT}$ be the required energy consumption

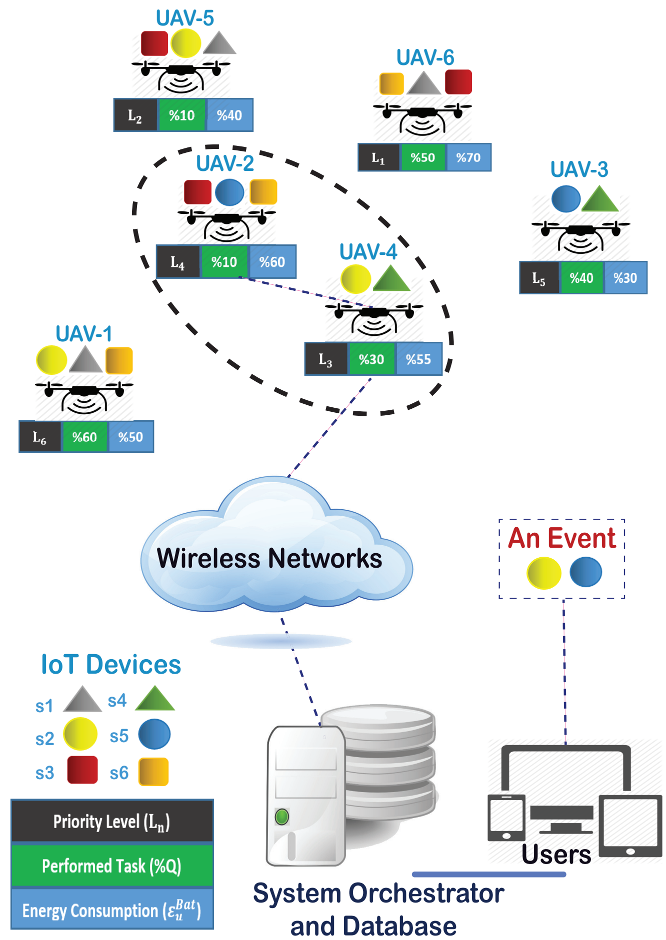

Figure 3. *UAV selection mechanisms based on different constraints.*

and operation time for a UAV u to handle an event $\mathcal{E}$, respectively. So that,

$$\xi_{u,\mathcal{E}}^{ToT} = \xi_{u,\mathcal{E}}^{Travel} + \xi_{u,\mathcal{E}}^{SenseProcess} + \xi_{u,\mathcal{E}}^{Transmit}, \tag{26}$$

where $\xi_{u,\mathcal{E}}^{Travel}$, $\xi_{u,\mathcal{E}}^{SenseProcess}$ and $\xi_{u,\mathcal{E}}^{Transmit}$ denote the UAV's energy consumption needed for the traveling, sensing-and-processing, and the data transmission, respectively. Accordingly,

$$\Upsilon_{u,\mathcal{E}}^{ToT} = \Upsilon_{u,\mathcal{E}}^{Travel} + \Upsilon_{u,\mathcal{E}}^{SenseProcess} + \Upsilon_{u,\mathcal{E}}^{Transmit}, \tag{27}$$

where $\Upsilon_{u,\mathcal{E}}^{Travel}$, $\Upsilon_{u,\mathcal{E}}^{SenseProcess}$ and $\Upsilon_{u,\mathcal{E}}^{Transmit}$ denote the time duration needed for the UAV's traveling, sensing-and-processing, and the transmission, respectively. In the optimization problems, let $\mathcal{X}_{u,\mathcal{E}}$ be a boolean decision variable that equals 1 if a UAV $u \in \ddot{\mathcal{N}}$ carries out an event $\mathcal{E} \in \mathcal{E}_L$; otherwise it equals 0.

$$\mathcal{X}_{u,\mathcal{E}} = \begin{cases} 1 & \text{If } u \text{ is selected to handle an event } \mathcal{E} \\ 0 & \text{Otherwise} \end{cases} \tag{28}$$

A. Optimization of the energy consumption

In this subsection, we propose a solution, dubbed Energy Aware UAV Selection (EAUS), that aims at minimizing as much as possible the energy consumption to handle the variant IoT events. In fact, the EAUS solution aims at selecting the minimum number of UAVs

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while ensuring that the time latency does not exceed a predefined threshold Υ_{th}. The EAUS solution is formulated through the following Linear Integer Optimization Problem (**OP1**):

$$\begin{cases} \textbf{min} \sum_{u \in \ddot{\mathcal{N}}} \sum_{\mathcal{E} \in \mathcal{E}_L} \xi_{u,\mathcal{E}}^{ToT} \cdot \mathcal{X}_{u,\mathcal{E}} \\ \textbf{s. t.} \\ \forall \mathcal{E} \in \mathcal{E}_L, \forall s \in \mathcal{S}_{\mathcal{E}} : \sum_{u \in \ddot{\mathcal{N}} \wedge s \in \mathcal{S}_u} \mathcal{X}_{u,\mathcal{E}} \geq 1 \\ \forall u \in \ddot{\mathcal{N}} : \Upsilon_{u,\mathcal{E}}^{ToT} \cdot \mathcal{X}_{u,\mathcal{E}} \leq \Upsilon_{th} \\ \forall \mathcal{E} \in \mathcal{E}_L, \forall u \in \ddot{\mathcal{N}}, \forall \mathcal{E}' \in \mathcal{E}_L, \mathcal{E} \neq \mathcal{E}' : \mathcal{X}_{u,\mathcal{E}} + \mathcal{X}_{u,\mathcal{E}'} \leq 1 \\ \forall \mathcal{E} \in \mathcal{E}_L, \forall u \in \ddot{\mathcal{N}} : \mathcal{X}_{u,\mathcal{E}} \in \{0,1\} \end{cases} \quad (29)$$

The objective of this optimization is to minimize the energy consumption of the selected UAVs. Meanwhile, the constraints of the optimization ensure the following statements. The first constraint ensures that the selected UAVs have the required IoT devices to deal with the events $\mathcal{E}_L$. The second constraint ensures that the time latency of each selected UAV $u \in \ddot{\mathcal{N}}$ should not exceed the threshold Υ_{th} when handling each event $\mathcal{E} \in \mathcal{E}_L$. The third constraint ensures that a UAV $u \in \ddot{\mathcal{N}}$ should not handle two different events at the same time. This means that one UAV cannot be at two variant locations at the same time. The last constraint ensures that $\mathcal{X}_{u,\mathcal{E}}$ is a boolean decision variable.

B. Optimization of the operation time

In this subsection, we present the second solution, named Delay Aware UAV Selection (DAUS), that aims at minimizing as much as possible the UAVs operation time while ensuring the expected energy consumption during the missions does not exceed a predefined threshold Υ_{th}. In fact, the DAUS solution aims at minimizing the operation time of the UAVs while maintaining the total energy consumption of UAVs below a predefined threshold ξ_{th}. This solution is formulated through the following Linear Integer Optimization Problem (**OP2**):

$$\begin{cases} \textbf{min} \quad \mathcal{Z} \\ \textbf{s. t.} \\ \forall \mathcal{E} \in \mathcal{E}_L, \forall s \in \mathcal{S}_{\mathcal{E}} : \sum_{u \in \ddot{\mathcal{N}} \wedge s \in \mathcal{S}_u} \mathcal{X}_{u,\mathcal{E}} \geq 1 \\ \sum_{u \in \ddot{\mathcal{N}}} \sum_{\mathcal{E} \in \mathcal{E}_L} \xi_{u,\mathcal{E}}^{ToT} \cdot \mathcal{X}_{u,\mathcal{E}} \leq \xi_{th} \\ \forall \mathcal{E} \in \mathcal{E}_L, \forall u \in \ddot{\mathcal{N}} : \Upsilon_{u,\mathcal{E}}^{ToT} \cdot \mathcal{X}_{u,\mathcal{E}} \leq \mathcal{Z} \\ \forall \mathcal{E} \in \mathcal{E}_L, \forall u \in \ddot{\mathcal{N}}, \forall \mathcal{E}' \in \mathcal{E}_L, \mathcal{E} \neq \mathcal{E}' : \mathcal{X}_{u,\mathcal{E}} + \mathcal{X}_{u,\mathcal{E}'} \leq 1 \\ \forall \mathcal{E} \in \mathcal{E}_L, \forall u \in \ddot{\mathcal{N}} : \mathcal{X}_{u,\mathcal{E}} \in \{0,1\} \end{cases} \quad (30)$$

The objective of this solution aims at minimizing the operation time of UAVs. Meanwhile, the constraints ensure the following statements. The first constraint ensures that the selected UAVs have the required IoT devices to deal with each event $\mathcal{E} \in \mathcal{E}_L$. The second constraint ensures that the energy consumption of selected UAVs should not exceed the threshold ξ_{th}. The third constraint aims to find the maximum operation time $\mathcal{Z}$. The fourth constraint ensures that each UAV $u \in \ddot{\mathcal{N}}$ should not handle two different events at the same time. The last constraint ensures that $\mathcal{X}_{u,\mathcal{E}}$ is a boolean decision variable.

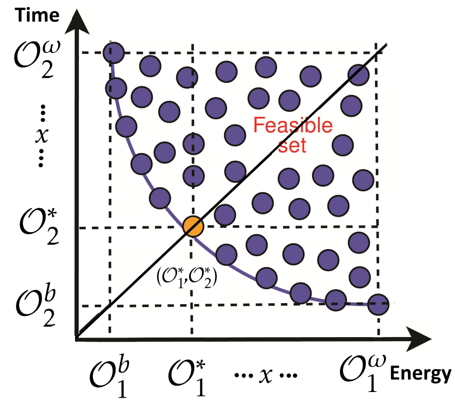

Figure 4. Our Solution (FTUS)- Bargaining.

C. Fair trade-off between the energy consumption and operation time using bargaining game

In this subsection, we propose a third solution, named Fair Trade-off UAV Selection (FTUS), that aims at finding a fair trade-off between the two conflicting objectives, which are the energy consumption and the operation time. It is worth noting that a bargaining game would be used to find a fair trade-off between the players (the conflicting objectives). Then, in FTUS, the energy consumption by UAVs and the operation time are considered as two players that would like to barter goods.

1) Cooperative games: In cooperative games, the players are assumed to attain either most desirable point when negotiation succeeds or disagreement point when negotiation fails. For the game, let we consider two persons game who would like to barter goods and each one of them wants to increase his benefits. Let Φ be the vector payoffs of theses players. Formally, $\Phi = \{(\mathcal{O}_1(x), \mathcal{O}_2(x)), x = (x_1, x_2) \in \mathcal{X}\}$, where $\mathcal{X}$ is the set of the two players' strategies and $\mathcal{O}_1(x)$ and $\mathcal{O}_2(x)$ represent the utility functions of the two players, respectively.

Nash Bargaining Model (NBM) [28] presents a cooperative game with non-transferable utility. This means that the utility scales of the players are measured in non-comparable units. Nash bargaining game is based on two elements assumed to be given and known to the players. The first element is the set of vector payoffs Φ achieved by the players if they agree to cooperate. Φ should be a convex and compact set. The second element is the threat point, $\omega = (\mathcal{O}_1^{\omega}, \mathcal{O}_2^{\omega}) \in \Phi$, which represents the pair of utility, whereby the two players fail to achieve an agreement. In NBM, the aim is to find a fair and reasonable point, $(\mathcal{O}_1^*, \mathcal{O}_2^*) = \mathcal{F}(\Phi, \mathcal{O}_1^{\omega}, \mathcal{O}_2^{\omega}) \in \Phi$. Based on Nash theory, a set of axioms [28] are defined that leads to find the unique pareto-optimal solution $(\mathcal{O}_1^*, \mathcal{O}_2^*)$. Moreover, the unique solution $(\overline{\mathcal{O}}, \overline{\mathcal{V}})$, satisfying these axioms, is proven to be the solution of the following optimization problem:

$$\begin{cases} \textbf{max} \quad (\mathcal{O}_1(x) - \mathcal{O}_1^{\omega})(\mathcal{O}_2(x) - \mathcal{O}_2^{\omega}) \\ \textbf{s. t.} \\ (\mathcal{O}_1(x), \mathcal{O}_2(x)) \in \Phi \\ (\mathcal{O}_1(x), \mathcal{O}_2(x)) \geq (\mathcal{O}_1^{\omega}, \mathcal{O}_2^{\omega}) \end{cases} \quad (31)$$

An enhanced solution of Nash bargaining game is Kalai-Smorodinsky Bargaining Solution (KSBS) [29]. The

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aim of KSBS is to enhance the fairness between the players by sharing the same utility fraction r among them. KSBS preserves the same Nash bargaining axioms except the independence of irrelevant alternatives. KSBS has also a new axiom called monotonically. In contrast to the Nash bargaining game and in addition to the disagreement point $\omega = (\mathcal{O}_1^{\omega}, \mathcal{O}_2^{\omega}) \in \Phi$, KSBS needs the ideal point $x^b = (\mathcal{O}_1^b, \mathcal{O}_2^b)/x^b \in \Phi$, the best utility that both players can achieve separately without bargaining. Kalai and Smorodinsky prove that the unique solution to satisfy KSBS's axioms is the solution of the following optimization problem:

$$\begin{cases} \mathbf{max}\ r \\ \mathbf{s.\ t.} \\ (\mathcal{O}_1(x), \mathcal{O}_2(x)) \in \Phi \\ r = \dfrac{\mathcal{O}_1(x) - \mathcal{O}_1^{\omega}}{\mathcal{O}_1^b - \mathcal{O}_1^{\omega}} \\ r = \dfrac{\mathcal{O}_2(x) - \mathcal{O}_2^{\omega}}{\mathcal{O}_2^b - \mathcal{O}_2^{\omega}} \end{cases} \tag{32}$$

D. FTUS description

In this subsection, we describe the solution FTUS. Let $\omega = (\mathcal{O}_D^{\omega}, \mathcal{O}_E^{\omega})$ and $b = (\mathcal{O}_D^b, \mathcal{O}_E^b)$ denote the threat and best points of the KSBS game for the energy consumption and the response time, respectively. As we have mentioned before, Υ_{th} and ξ_{th} denote the threshold values of the operation time and the energy consumption, respectively. In a KSBS game, both players, i.e., energy and delay, should bargain for increasing their benefits, which is in conflict with and opposite to their utility function defined by the optimization problems (**OP1**) and (**OP2**). In a bargaining game, both players aim to increase their utility functions. However, in our case, both players (operation time and energy consumption) aim to reduce their values. Formally, the lower the values of the operation time and energy consumption are, the better the utility functions become. In order to use the KSBS game for ensuring a fair trade-off between the operation time and the energy consumption (Fig.4), we have inversed the utility function to be the smallest values better for both players. The fair Pareto optimal solution FTUS is formulated as follows:

$$\begin{cases} \mathbf{max}\ r \\ \mathbf{s.\ t.} \\ \forall \mathcal{E} \in \mathcal{E}_L, \forall s \in \mathcal{S}_{\mathcal{E}} : \displaystyle\sum_{u \in \ddot{\mathcal{N}} \wedge s \in \mathcal{S}_u} \mathcal{X}_{u,\mathcal{E}} \geq 1 \\ \displaystyle\sum_{u \in \ddot{\mathcal{N}}} \sum_{\mathcal{E} \in \mathcal{E}_L} \xi_{u,\mathcal{E}}^{ToT} \cdot \mathcal{X}_{u,\mathcal{E}} \leq \mathcal{O}_E^{\omega} \\ \forall \mathcal{E} \in \mathcal{E}_L, \forall u \in \ddot{\mathcal{N}} : \Upsilon_{u,\mathcal{E}}^{ToT} \cdot \mathcal{X}_{u,\mathcal{E}} \leq \mathcal{O}_D^{\omega} \\ \forall \mathcal{E} \in \mathcal{E}_L, \forall u \in \ddot{\mathcal{N}}, \forall \mathcal{E}' \in \mathcal{E}_L, \mathcal{E} \neq \mathcal{E}' : \mathcal{X}_{u,\mathcal{E}} + \mathcal{X}_{u,\mathcal{E}'} \leq 1 \\ \forall \mathcal{E} \in \mathcal{E}_L, \forall u \in \ddot{\mathcal{N}} : \Upsilon_{u,\mathcal{E}}^{ToT} \cdot \mathcal{X}_{u,\mathcal{E}} \leq \mathcal{O}_D(x) \\ \mathcal{O}_E(x) = \displaystyle\sum_{u \in \ddot{\mathcal{N}}} \sum_{\mathcal{E} \in \mathcal{E}_L} \xi_{u,\mathcal{E}}^{ToT} \cdot \mathcal{X}_{u,\mathcal{E}} \\ r = \dfrac{\mathcal{O}_D^{\omega} - \mathcal{O}_D(x)}{\mathcal{O}_D^{\omega} - \mathcal{O}_D^b} \\ r = \dfrac{\mathcal{O}_E^{\omega} - \mathcal{O}_E(x)}{\mathcal{O}_E^{\omega} - \mathcal{O}_E^b} \\ \forall u \in \ddot{\mathcal{N}} : \mathcal{X}_{u,\mathcal{E}} \in \{0,1\} \end{cases} \tag{33}$$

V. Performance Evaluation

In this section, we evaluate the three proposed solutions EAUS, DAUS and FTUS, using Python and Gurobi optimization tools. In the simulations, each plotted point represents the average of 100 times executions. The plots from these simulations are presented with 95% confidence interval.

A. Network Parameters

In the simulations, the solutions are evaluated in terms of the following criteria: the energy consumption, the operation time, and the execution time. While the first and second evaluations are based on the energy and operation time of UAVs for accomplishing IoT tasks, the third criteria evaluates the required time for executing each solution. The variant solutions are evaluated by varying: i) the number of UAVs; ii) the size of UAVs flying area; iii) the number of events; and iv) the types of IoT devices in the network (i.e., the IoT devices required by different events). We have considered four levels of priorities of events. The maximum flight altitude of UAVs is set to 150 meters. For the UAV communications, for the transmission power P_t, we have used a uniform distribution between 10 and 15 W. We set the other parameters based on Table II, which we adopt from the studies [30] and [31]. To model the UAV communications in urban environments, the study in [30] takes into account the shadowing effect and path loss as in our UAV communication model. In addition, to apply a precise value for UAV communications in urban environments, we have adopted the value presented in [31] for the standard deviation that is achieved by the experiments.

Table II
The values utilized for UAV's communication.

$\mathcal{D}_0$	$\mathcal{D}_{u,\mathcal{B}}$	φ	K	$\sigma_{\psi_{dB}}$	γ_{th}
1 m	30 m	2	-30 dB	8.1 dB	-120 dBm

To perform a near-to-realistic study in the simulations, we consider the following intervals for the varying parameters for the three solutions. In Fig. 5, the proposed solutions are evaluated by varying the number of UAVs from 50 to 800 while setting: i) the number of events to 50; ii) the size of area to 900 km^2, and iii) the number of IoT devices to 10 (onboard the UAVs and required by the events). Fig. 6 shows the performance of the three solutions by varying the size of the deployed area from 20 km^2 to 2500 km^2 while fixing: i) the number of UAVs to 400, ii) the number of events to 50, and iii) the number of IoT devices to 10. Fig. 7 illustrates the performance of the proposed solutions by varying the number of IoT devices while setting: i) the number of UAVs to 400, ii) the number of events to 50, and iii) the size of area to 900 km^2. The number of IoT devices is randomly selected from the interval [5,100]. Fig. 8 shows the performance of the three solutions by varying

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the number of events from 10 events to 150 events and fixing: *i*) the number of UAVs to 400; *ii*) the size of area to 900 km^2, and *iii*) the number of IoT devices to 10. In fact, for the number of UAVs, we have used the interval [50, 800] which shows reasonable numbers of deployed UAVs when the area size is fixed to 900 km^2. For the size of UAVs flying area, we have used the interval [20, 2500] km^2 where we have considered the maximum flight range for some UAVs which is 50 km^2. We have chosen this interval due to the fact that the flight ranges (maximum flight times) of civilian UAVs is related to their model, which can vary from 4 *km* till 50 *km*, and even more for some UAVs. Therefore, the flight ranges of all of the existing UAVs in the network make them eligible to be selected for handling an event $\mathcal{E}$. This is so that the selected UAVs can fly from their current location to the location of the event within the selected interval.

For the number of events, we have used the interval [10, 150] that is reasonable when the size of area is fixed to 900 km^2. For the types of IoT devices, we have used the interval [5, 100] that is also reasonable when the number of UAVs and the number of events are set to 400 and 50, respectively. In the simulations, each UAV and each event involve 10 different IoT devices that have variant types and should be selected from a predefined interval. Formally, if we fix the interval of IoT devices to a lower range than the used one, the UAVs would have similar IoT devices. Thus, any UAV can handle the events, and hence the optimal solutions will end up selecting the UAVs that are closest to the events' locations, which is a trivial solution. Then, setting the interval [5, 100] for IoT devices will i) allow assigning diverse types of IoT devices for the UAVs and the events, ii) enable distributing them in an efficient manner, and iii) give the possibility to select the UAVs at distant locations to handle a specified event. In this way, simulations will offer more possibilities for effectively evaluating the proposed solutions. In addition, Figs. 9(a) – 9(d) depict the system execution times of the three solutions with the corresponding system parameters as in Figs. (5) – (8), respectively.

B. Simulation Results

In this subsection, we discuss the performance of the proposed solutions in terms of energy consumption, the operation time, and the execution time, separately.

1) The energy consumption of UAVs: The simulation experiments, shown in Figs. 5.(a) - 8.(a), present the performance evaluation of the three solutions, i.e. EAUS, DAUS, and FTUS, when the objective is to minimize the total energy consumption of the UAVs. Fig. 5.(*a*) shows that when the number of UAVs in the network increases, the EAUS solution demonstrates the best performance by reducing the total energy consumption of the UAVs. Obviously, in a fixed size of the area, when the number of UAVs to handle a certain number of IoT events increases, the number of eligible UAVs which are close to the IoT events becomes higher. In this way, the high availability of eligible UAVs reduces the traveling distances of UAVs, which are the major sources of UAVs energy consumption. From this figure, we also observe that increasing the number of UAVs has a negative impact on the energy consumption when applying the DAUS solution. This is due to the reason that DAUS is designed to reduce the operation time of the UAVs without considering their energy consumption. Thus, by increasing the number of UAVs, DUAS will select a high number of UAVs to reduce the total operation time, unaware of the fact that the overall energy consumption increases. The figure also shows the performance of the FTUS solution. Let us recall that FTUS aims at finding a fair trade-off between energy consumption and operation time. Therefore, when the objective is to minimize the energy consumption, in contrast to DAUS, with an increase in the number of UAVs in the network, FTUS exhibits performance similar to that of EAUS.

The simulations in Fig. 6.(a) depict the impact of increasing the size of area on the UAVs overall energy consumption by the three solutions. This figure shows that increasing the size of the area does not have high impact on the energy consumption when applying the EAUS solution. Since the number of UAVs is fixed to a high number, i.e. 400, the probability of selecting eligible UAVs near to the location of the event is high. This means that the distances between the UAVs to the location of event are short and less energy is consumed for the UAVs travellings. Thus, the impact of the size of area on the energy consumption when applying the EAUS solution is minimal. Meanwhile, this figure demonstrates that the increase in the number of UAVs has a negative impact on energy consumption in case of the DAUS solution. The DAUS solution is designed to minimize the operation time of the UAVs without taking into account their energy consumption. Increasing the size of the area, the DAUS solution selects the UAVs that can handle an IoT event at the shortest time. Applying DUAS, some UAVs that are at distant locations but would handle the IoT event in a shorter may be selected. In contrast, there may be eligible UAVs near to the location of the event that would need more operation time to perform a task. Thus, selecting the UAVs that are at distant locations results in high energy consumption by the UAVs. In addition, the third solution, i.e. FTUS, depicts a behavior similar to that of EAUS in terms of energy consumption.

The simulations in Fig. 7.(a) shows the impact of increasing the number of IoT devices on the total energy consumption of the UAVs. From this figure, we observe that the energy consumption in case of EAUS increases slightly from 40 to 60 *mAh*. The DAUS solution shows a rapid increase from 50 to 250 *mAh*, which is against

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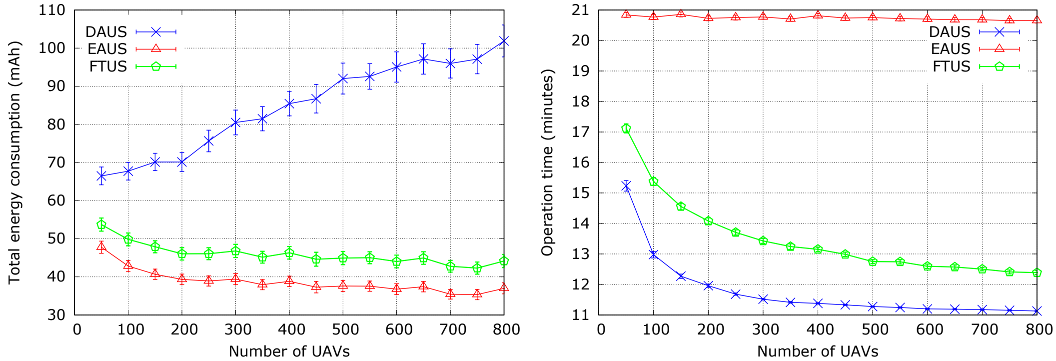
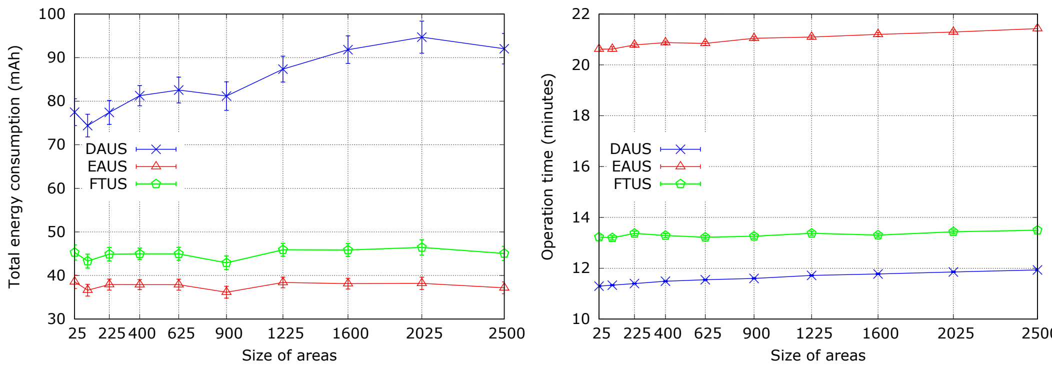


(a) The energy consumption

(b) The operation time

Figure 5. Performance of the proposed solutions as a function of the number of UAVs.



(a) The energy consumption

(b) The operation time

Figure 6. Performance of the proposed solutions as a function of the size of areas (km^2).

the energy consumption saving. That is due to the fact that when the number of IoT devices increases, the EAUS solution selects the devices that require less energy to handle the tasks. Instead, the DAUS solution does not take into account the energy consumption of the IoT devices and selects the devices that perform the tasks in a shorter time. Therefore, IoT devices with high energy requirements would be selected that results in a rapid increase in energy consumption. In addition, the trade-off between the two solutions, i.e. FTUS exhibits performance similar to that of EAUS. Furthermore, the simulations in Fig. 8.(a) illustrate the performance of the three solutions when increasing the number of events in the network. The simulations illustrate that an increase in the number of events has a negative impact on energy consumption. We observe that both EAUS and FTUS have better performance than DAUS in terms of energy consumption. All in all, the obtained results demonstrate the superiority of the EAUS and FTUS solutions in terms of energy consumption and that is in comparison to the DAUS solution. Noting that an increase in the number of events increases the total energy consumption and the operation time by the UAVs. This results in a gradual increase when applying the three solutions.

2) The operation time: The simulations presented in Figs. 5.(b) - 8.(b) show the performance of the three solutions, i.e., EAUS, DAUS, and FTUS, in terms of the UAVs' operation time. The simulations in Fig. 5.(b) show the impact of increasing the number of UAVs on the total operation time. We observe that the increase in the number of UAVs has a positive impact on the operation time when applying the DAUS and FTUS solutions. In fact, increasing the number of UAVs in the network increases the number of eligible UAVs close to the locations of the IoT events. Thus, the UAVs that can handle the events in a shorter time would be selected to perform the tasks. In such a way, the total operation time of UAVs will be minimized. In contrast to DAUS and FTUS, the aim of the EAUS solution is to save the energy consumption without taking into account the UAVs operation time. For this reason, EAUS shows the worst performance when the objective is to minimize the UAVs operation time.

The simulations in Fig. 6.(b) illustrate the impact of increasing the size of the flying area on EAUS, DUAS, and FTUS when the objective is to minimize the UAVs operation time. From the simulation results plotted in this figure, we observe that the performance of both DAUS and FTUS are much better than the EAUS solution. This is due to the fact that the DAUS solution aims to reduce the operation time of the UAVs without considering their energy consumption. The simulations in Fig.7.(b) demonstrate the impact of varying the number of IoT

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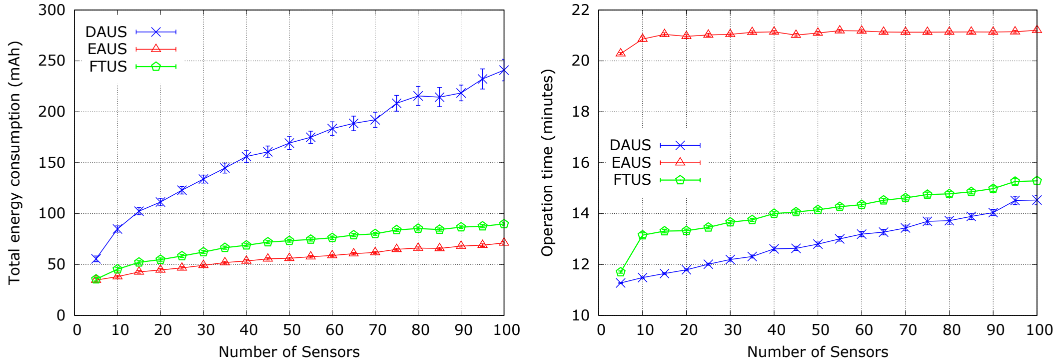
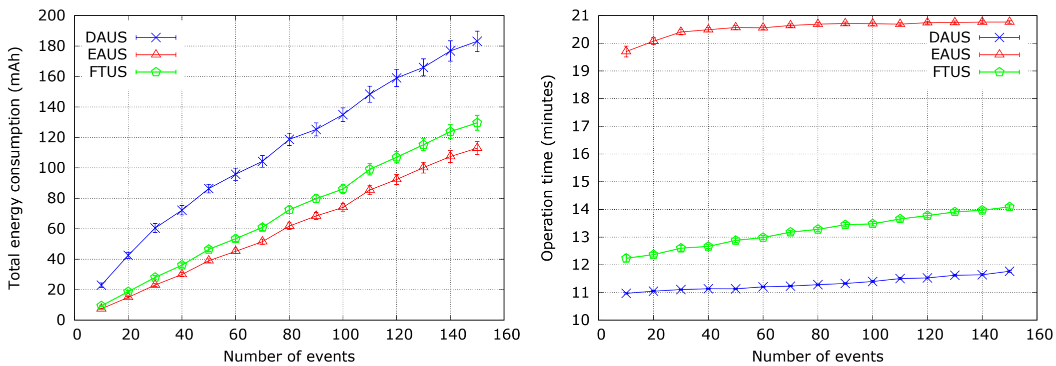


(a) The energy consumption

(b) The operation time

Figure 7. Performance of the proposed solutions as a function of the number of sensors (i.e., IoT devices).



(a) The energy consumption

(b) The operation time

Figure 8. Performance of the proposed solutions as a function of the number of events.

devices on the operation time for each of the solutions. We observe that enhancing the number of IoT devices in the network gradually raises the operation times of both the DAUS and FTUS solutions, resulting in a negative impact. Actually, each IoT device needs a specific operation time to perform the assigned task. Therefore, increasing the number of IoT devices for an event will substantially affect the amount of the required operation time. In addition, the DUAS and FTUS solutions have better performance than EAUS. This can be explained as follows. EAUS is designed to minimize the energy consumption without taking into account the operation time.

In addition, the simulations in Fig. 8.(b) demonstrate the performance of the three solutions in terms of the operation time when increasing the number of IoT events in the network. From this figure, we observe that both DAUS and FTUS exhibit better performance in comparison to EAUS. We also observe that when the number of events increases, the total operation time of the UAVs slightly enhances. In fact, deploying 400 UAVs over an area of a size of $900km^2$ is good enough to find eligible UAVs to handle events within the range $[10, 150]$ while spending a short operation time. The results obtained from the simulations, illustrated in Figs. 5.(b) - 8.(b), clearly highlight the superiority of both the DAUS and FTUS solutions over the EAUS solution when the objective is to minimize the UAVs operation time. The obtained results from the evaluated simulations confirm the efficiency of each solution in achieving its main design objectives. These results also prove the efficiency of FTUS in achieving a fair trade-off between energy consumption and operation time.

3) The execution time: Figs. 9(a)-(d) show the execution times of the three solutions for different system input parameters when increasing the number of UAVs, size of areas, number of IoT devices, and number of events. As shown in the figures, in all evaluations, EAUS has the best performance in terms of execution time. The execution time of DAUS is twice that of EAUS, while FTUS needs longer execution time. As a matter of fact, the execution time of EAUS is shorter than that of DAUS since the optimization problem of EAUS is formulated using fewer constraints. DAUS uses four sets of constraints while EAUS is formulated with three sets of constraints. In addition, FTUS needs more execution time than DAUS and EAUS due to the following facts: i) it is formulated with nine constraints and ii) it needs the execution of both solutions to perform the trade-offs (i.e. getting the threat and best points). The results in Figs.

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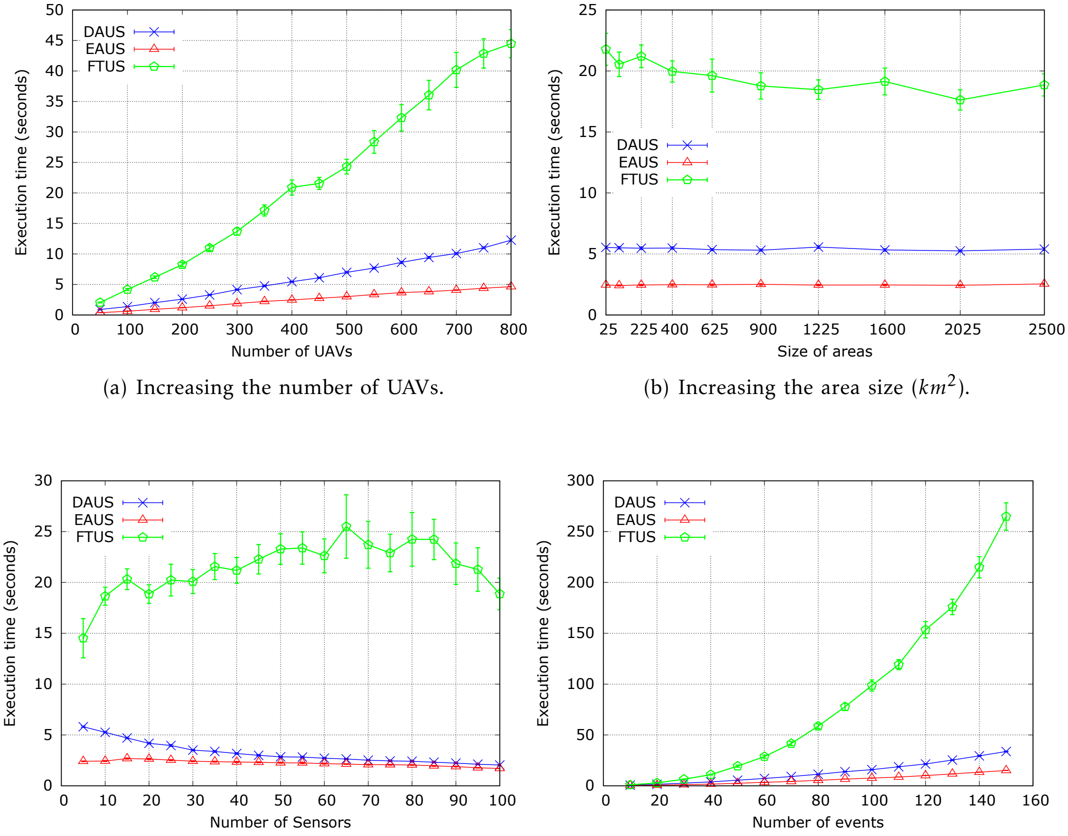

(a) Increasing the number of UAVs.

(b) Increasing the area size (km^2).

(c) Increasing the number of sensors.

(d) Increasing the number of events.

Figure 9. The system execution time.

9(a), 9(c) and 9(d) show that an increase in the number of UAVs, the number of IoT devices, and the number of events has a negative impact on the execution times for the FTUS solution. This is due to the fact that increasing those parameters leads to an increase in the number of variables and constraints on the optimization problems, which, in its turn, has a negative impact on the execution time. Furthermore, Fig. 9(b), which refers to the increase in the size of flying areas, does not have any impact on the execution time. Referring to the proposed solutions defined in (29), (30), and (33), the constraints that have formed these solutions are defined by the number of UAVs, the number of IoT devices, and the number of events. Therefore, in the simulations, the size of the area increases but the number of variables and constraints remain the same. As a result, increasing the size of flying area will not have an impact on the system execution time.

VI. Conclusion

UAVs can be used to provide diverse services from the sky. While each UAV may be used to perform a specific task, having the UAVs equipped with different IoT devices creates additional benefits in the form of VAIoTS for their operators. This VAIoTS can be configured by a central system orchestrator that has the information about the flying UAVs, e.g. their current positions and their onboard IoT devices. To select an appropriate UAV to handle an IoT task, critical parameters such as the UAV's position, its energy budget and its equipment have to be taken into account.

In this paper, we presented a robust system orchestrator (SO) that is designed to provide VAIoTS. To perform an efficient UAV selection mechanism for providing VAIoTS through the SO using linear integer problems, we proposed three solutions: EAUS, DAUS, and FTUS. EAUS aims at reducing the total energy consumption by the UAVs, DAUS aims at decreasing the UAVs operational time, and FTUS finds a fair solution between the two conflicting objectives of energy and time. The performance of the three optimizations is evaluated by varying four parameters: varying the number of UAVs, increasing the size of the flying area, varying the number of IoT events, and increasing the types of IoT devices onboard the UAVs and for the events. In the simulations, each time we fixed two of these parameters, we varied the other two parameters against each other.

The first observation from these variations is that when the number of IoT devices onboard UAVs and the number of IoT events in the UAV network are fixed: i) increasing the number of UAVs in a fixed size of area has a positive impact on reducing the energy consumption as well as on reducing the operation time by the UAVs; ii) on the contrary, increasing the area size while keeping a fixed number of UAVs does not have much impact on the energy consumption nor on the operation time. The second observation from the variations is that while the number of UAVs and the area size in UAVs network are fixed: i) increasing the number of IoT devices with a fixed number of IoT events slightly increases the energy consumption as well as the operation time by the UAVs; ii) however, increasing the number of IoT events with a fixed number of onboard IoT devices slightly increases the UAVs' operation time, but rapidly enhances the UAVs' energy consumption.

Furthermore, the observations of the performance evaluation from the proposed solutions demonstrate that when the objective is to minimize the total energy consumption by the UAVs, EAUS shows the best performance. Similarly, when the objective is to minimize the total UAVs operation time, DAUS demonstrates the best performance. In addition, when the aim is to find a fair solution between EAUS and DAUS, the FTUS scheme offers the best solution. In fact, the evaluation of the simulation results proves the efficiency of each solution in achieving its key design objectives. The achieved results from the simulations confirm the suitability of our proposed UAV selection mechanisms to be integrated into the envisioned system orchestrator.

As future work, we plan to improve the modeling part considering any possible source of energy consumption, e.g. UAVs GPS energy consumption considering the GPS localization errors and signal losses. In the new model, we will take into account the case of accidents and UAVs failures to complete an IoT task. In addition, we plan to consider a set of UAVs that share all of their resources (i.e. storage, transmission, and computing capabilities) to perform multiple tasks in parallel. In addition, we will consider self-aware UAVs that can estimate their residual energy amount to inform their candidacy for handling the next task.

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