Distributed CNN Inference on Resource-Constrained UAVs for Surveillance Systems: Design and Optimization

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Abstract—Unmanned Aerial Vehicles (UAVs) have attracted great interest in the last few years owing to their ability to cover large areas and access difficult and hazardous target zones, which is not the case of traditional systems relying on direct observations obtained from fixed cameras and sensors. Furthermore, thanks to the advancements in computer vision and machine learning, UAVs are being adopted for a broad range of solutions and applications. However, Deep Neural Networks (DNNs) are progressing towards deeper and complex models that prevent them from being executed on-board. In this paper, we propose a DNN distribution methodology within UAVs to enable data classification in resource-constrained devices and avoid extra delays introduced by the server-based solutions due to data communication over air-to-ground links. The proposed method is formulated as an optimization problem that aims to minimize the latency between data collection and decision-making while considering the mobility model and the resource constraints of the UAVs as part of the air-to-air communication. We also introduce the mobility prediction to adapt our system to the dynamics of UAVs and the network variation. The simulation conducted to evaluate the performance and benchmark the proposed methods, namely Optimal UAV-based Layer Distribution (OULD) and OULD with Mobility Prediction (OULD-MP), were run in an HPC cluster. The obtained results show that our optimization solution outperforms the existing and heuristic-based approaches.

Index Terms—Unmanned Aerial Vehicles, Distributed Machine Learning, Deep Neural Networks, Convolutional Neural Network.

I. INTRODUCTION

In the last decade, UAVs have been proposed as an alternative to the traditional technologies involved in a plethora of applications ranging from large-scale agriculture in search of weeds and pests [1], goods delivery [2], and wild life recording [3] to smart city monitoring [4] and rescue operations [5]. Meanwhile, technologies that have been used to remotely monitor large areas such as Satellite Remote Sensing (SRS) and Sensor Networks (SNs) are losing interest against UAVs [6]. This revolutionary advancement in the monitoring systems is related to the maturity of UAVs and the challenges that both aforementioned technologies encounter, including the implementation cost, the non-ability to perform close monitoring for the case of SRS systems, the permanent deployment of sensors, and the need for constant human intervention and maintenance for the case of SNs. Hence, driven by the need for better scene coverage and prompt interventions in case of incidents, UAVs are proposed as a new innovative and cost-effective solution for low altitude sensing with zero deployments. Additionally, UAVs present a rapid and flexible data acquisition system that can provide close monitoring of human activity and objects from different angles and altitudes, resulting in high-resolution data used to enhance complex events detection.

Such distinctive performance of drones encouraged the emergence of more critical and sophisticated missions in uncertain and potentially harsh environments, many of them was not even envisaged a couple of decades ago, including military border surveillance and oil/gas offshore inspection [7]. Some of these solutions require more than one UAV to grant higher system reliability and scalability, and ensure dynamic and flexible surveillance [8]. More specifically, the swarm of drones equipped with different types of sensors are distributed in the mission zone to gather the real-time data and report the on-site information to the command center in order to take immediate measures. Another major advantage of a UAV swarm is the ability to handle more complex operations by distributing and performing parallel tasks to reduce the execution time and guarantee a better fault tolerance [9].

In surveillance applications, the aim is to monitor specific ground objects or identify threats within the target region. Thus, unlike satellite imagery, higher data resolution should be gathered, specially for a security plan [10]. In this context, UAVs are the most suitable technology to provide such fine-grained data about the target object from different angles, which makes the identification more accurate [11]. These data-generating devices are only responsible for collecting the data, while servers with higher capacities generate the identification results using Artificial Intelligence (AI) techniques. The traditional wisdom resorts to cloud or edge servers to compute heavy tasks. However, due to the harsh environments where UAVs flow (e.g., military border zones, forests, offshore oil reserves, etc.), the communication with remote servers is strongly affected by the weather. Also, the processing might be difficult or even impossible because of the interference resulting from the UAV altitude and the underground environment (e.g., high-rise building effect on path loss) [12].
Furthermore, as UAVs are sending high-resolution images to cloud/edge servers at each small interval of time and knowing that incidents are rarely occurring, the large data volume transmitted by source units has become problematic, particularly for systems that do not have stable bandwidth availability [13]. Because of this tremendous amount of data obtained during the UAVs mission including those used to detect objects of interest or to perform accurate navigation, AI should be integrated into the design of UAVs [14].

Deep Neural Networks used in computer vision to process data gathered by UAVs have been significantly improved in the last few years [15]. This advancement has not been followed by the improvement of computation capabilities of UAVs. As an example, recent models are progressing toward deeper neural networks with higher computation demands, which is illustrated in table I. Even though deep learning has achieved substantial breakthroughs in UAVs applications, it is still challenging to implement the complex DNN models in a single resource-constrained device, because of their computation requirements resulting in unfeasible execution time [16].

### TABLE I: Progression towards deeper neural network structures in recent years.

| Architecture Name | Year | Parameters | Depth | Reference |
|-------------------|------|------------|-------|-----------|
| LeNet             | 1998 | 0.860 M    | 5     | [13]      |
| AlexNet           | 2012 | 60 M       | 8     | [18]      |
| VGG               | 2014 | 138 M      | 19    | [19]      |

In order to fit the requirements of DNN into the resource-constrained devices, collaborative deep learning strategies have been recently proposed in the literature. The basic idea is to divide the DNN model into segments (e.g., layers, multiplication tasks, etc.) and each segment is allocated within a participant. Each participant shares the output to the next one until generating the final prediction. In this way, the entire inference can be locally performed at the proximity of the data source, without the need to transmit the original data to the remote servers. Nevertheless, the existing efforts mainly explored different possible partitioning that allows deploying DNN models on resource-limited devices (e.g., IoT devices, sensors, etc.). However, scheduling the communication between participants and designing a collaboration strategy to conduct inference tasks, while being constrained by computation and memory were not considered by previous works. Furthermore, accomplishing in-site classification by moving devices exposed to path loss and potential disconnection, has not been studied in the literature. Therefore, to support deep neural processing in UAV systems, the DNN distribution must be redesigned in order to consider hardware and physical constraints as well as planned paths and communications loss, which will be done in our work.

In this paper, we study surveillance systems and we consider Convolutional Neural Networks (CNNs), as they demonstrated unprecedented efficiency for image classification. To match resource-consuming DNN solutions with the constraints of UAV devices, we leverage the hierarchical design characterizing deep learning models, in order to suitably place layers of different classification requests. Particularly, we propose an approach that receives as an input the set of CNN classification requests (whose model is previously trained), the technological characteristics of the deployed UAVs, and the planned paths for different devices; and gives as an output the optimal placement of layers within participants, while having as an objective to minimize the latency of classification tasks which is the delay spent for executing the distributed inference and the delay to communicate the intermediate data. To the best of our knowledge, we believe that we are the first to exploit the distributed resources within surveilling UAVs to perform local inferences without compromising the accuracy of results. Our proposed methodology is validated for multiple state of the art CNN models and different requests’ loads and area sizes. The proposed approach also covers a large variety of applications, including public safety and control in smart cities where the transmission frequency is high or surveillance in harsh environment such as military zones and forests where the frequency bands are relatively low. The contributions of our paper are presented as follows:

- We present our system model that consists of multiple drones, responsible for capturing scenes and processing CNN classifications.
- We formulate our UAV collaborative inference as a non-linear optimization problem that aims to minimize the classification latency with stationary participants (i.e. relative distances between UAVs are stationary), while respecting the limited available resources. Due to the complexity of the problem, we convert the non-linear integer optimization into a linear one following the big-M rules [20].
- To cover the non-homogeneous variation of the relative distances between UAVs, the stationary solution must be run multiple times to handle the topology variation of devices during the swarm movement, which introduces an additional delay to the decision-making latency and increases the complexity of the problem. For these reasons, we tailor this method to include the non-homogeneous mobility model in order to predict the future location of each UAV.
- We conduct extensive simulations to evaluate the performance of our approach under different network configurations, e.g. requests load, area dimension, etc. We illustrate that executing multiple requests using the moving devices is possible and we unveil different parameters that should be present to achieve the maximum performance, including the number of devices, their capacities, and the deployed CNN networks.

Our paper is organized as follows: Section II explores relevant related works. Section III presents our proposed framework and the problem formulation under stationary and dynamic environments. The experimental evaluation is provided in section IV. Finally, in section V we draw the conclusions.

### II. RELATED WORKS

The advances in sensors’ capabilities, e.g., cameras, endowed with the UAVs have enabled these devices to play a vital role in a new breed of services and applications that
require unmanned operations. Recently, the integration of deep learning in UAV systems has leveraged the intelligence for addressing different challenging issues in these applications, and promising unprecedented performance and complexity reduction. As an example, authors in [21] introduced a strategy to detect forest fires, relying on machine learning techniques. The proposed approach combines the high-performance resources of cloud servers, the rich resources of edge computing and the sensing capacities of drones to capture the incident scene, interpret it in the remote servers, and perform early forest fire detection. However, as UAVs are sending high-resolution images to cloud/edge servers in small intervals of time, the large data volume transmitted by source units has become problematic, particularly for systems with fluctuating bandwidth stability. Because of these tremendous data obtained during the UAVs mission, several efforts proposed integrating AI into the design of UAVs, including the works in [22] and [23]. These efforts propose to utilize the on-board processing capabilities equipped with the UAVs to execute small-scale CNN networks such as YOLOv3-tiny. However, the testing results showed that the recognition accuracy is not sufficiently high. Additionally, due to the limited available resources, the classification latency does not match the real-time requirements of some applications, particularly those that need prompt interventions.

Several efforts have been conducted to fit deep neural networks in resource-constrained devices, from storage, computation, or hardware perspective. A promising technique that has been proposed in the literature, is compression. Such an approach aims to compact the existing state of art DNNs, while minimizing the accuracy loss. Pruning [24] is one of the compression approaches that consists of removing redundant weights/channels of smaller importance in the classification process. Quantization [25] is another technique that proposes to reduce the number of bits required to represent the activation of the model. Finally, Binarization [26] proposes to use binary values for weight and activation design. Even though the compression proved its capacity to integrate deep learning tasks in resource-constrained devices, this technique suffers from accuracy loss and cannot be applied to all types of dataset, neither supported by all devices.

In order to fit the requirements of DNNs into small devices without sacrificing the accuracy of the results, collaborative deep learning strategies have been recently proposed. More specifically, the deep neural network is divided into segments and each segment is executed within a helper. Different IoT frameworks have been proposed for CNN partitioning such as TensorFlow [27], DeepX [28], and Distributed Artificial Neural Networks for the Internet of Things (DIANNE) [29]. These solutions provide per layer distribution and require manual configuration from the user. In addition to the proposed distribution tools, multiple efforts have focused on the partitioning strategy that enables the implementation of large networks on small devices, e.g. sensors. Efforts dealing with DNN partitioning can be classified into three categories: First, many recent works, such as [30] aimed at minimizing the transmitted data to the remote servers. Thus, they proposed to compute shallow layers on constrained devices and delegate deep layers to the cloud/edge computing. The logic behind this technique is that intermediate data generated by deep layers are reduced compared to the original data. Furthermore, shallow layers do not require high computation capacities. Second, other approaches adopted the hierarchical architecture, where the model is distributed among cloud, edge and mobile units [31]. Even if resorting to remote computations can be a solution to minimize the delivered data, the transmission latency can prevent the implementation of such approaches, particularly in applications with low-delays requirements or with high classification demands. The third approach consists of relying only on pervasive devices to execute the inference requests at the proximity of the data source. In this context, two partition techniques are introduced: either to adopt per-layer distribution or to apply per-input partitioning (e.g., rows or columns of feature maps). Authors in [32] proposed per layer CNN distribution for IoT systems, where devices are known by their technological constraints. These resource-limitations
prevent them from locally executing the inference on the gathered data. Hence, a methodology to distribute multiple CNNs is proposed while optimizing the latency between data gathering and decision making. Authors in [33] proposed a per-input partition scheme for pre-trained DNN models to fit with resource-constrained mobile devices and accelerate DNN computations. In this method, the data delivery time between devices is minimized while considering two types of DNN layers and heterogeneous mobile devices which are used as computing resources. A study conducted in [34] proved that wireless sensor networks can be used as a hardware platform to implement parallel and distributed neurocomputing. This architecture is designed by mimicking the biological neural networks that exist in the brain. In this way, each sensor serves as the processing unit of an artificial neuron. DeepThings framework proposed in [35] provides adaptively distributed inference of CNN model on tightly resource-constrained IoT edge clusters. This framework uses the Fused Tile Partitioning (FTP), which is an input-wise division technique designed to reduce the memory footprint while ensuring parallelism.

Our proposed method is distinguished from the aforementioned approaches by several points: (1) The efforts that focused on re-designing the model or exploiting the hardware efficiently to fit the CNN networks in resource-constrained devices, such as compression, are sacrificing the accuracy. This is not the case of our approach that preserves accuracy, as no modification of the CNN characteristics is introduced during the distribution. Instead, we distribute a high-performance trained model with proven efficiency for scene classification. (2) The input-wise distribution or the per-neuron distribution are designed for highly limited-resources IoT devices or for sensor networks that are not even able to execute layers of advanced CNN models. Furthermore, these methods are implemented in large pervasive systems that include hundreds of devices and require a large dependency between participants to receive the outputs of different segments. This strategy cannot be applied to the UAV networks due to their low density (small number of drones) and the cost of dependency on air-to-air communication in terms of connectivity, latency, and consumed bandwidth. (3) The previously-described works proposed a static distribution of CNN models, such as each subset of devices is responsible to process a specific portion of the CNN model. This does not fit our online system, where a dynamic incoming load is received randomly during the surveillance mission and the connected UAVs must cooperate to autonomously parallelize all requests and optimally leverage the available resources, without being constrained by a static planned partitioning. Moreover, UAVs are moving units that can encounter disconnection situations, which makes static distribution invalid in our scenario. (4) To the best of our knowledge, we are the first to investigate real-time CNN inference distribution over a UAVs network, while considering the distinctive characteristics of air-to-air communication.

III. DISTRIBUTED CNN ON RESOURCE-CONSTRAINED UAVS

In this section, we present our distributed convolutional neural network approach for resource-constrained UAV devices and low decision-latency applications. For that, we start by designing our system model. Subsequently, we formulate this problem as an optimization, aiming at minimizing the total latency to execute the incoming classification requests. As we are dealing with moving devices, we next update our model to consider a UAVs’ mobility model and the data-rate variation of different participants.

A. System model

We consider a group of UAVs that are capable of forming a wireless ad hoc network. The network is composed of a set of $N$ UAVs, namely $\mathbb{N}_N$, as illustrated in Figure 1. These UAVs are responsible for monitoring a target area by capturing images and requesting data classification (e.g., detecting forest fires, detecting highway accidents, etc.). Two types of communication may occur in our network: UAV to UAV (U2U) and UAV to Ground device (U2G or Ground device to UAV) in order to connect to remote servers and send incident alarms. In our work, we will focus only on the U2U communications. The UAVs, deployed in the region under surveillance, are equipped with different IoT devices, such as cameras and GPS [36]. Moreover, each one of them can be either a data-generating node or/and a computation unit. Particularly, the data-generating node is responsible for gathering the data using its embedded camera and requesting the inference of the captured image, while the computation unit is a UAV performing a sub-task of the inference. Each UAV $i \in \mathbb{N}_N$ is characterized by a limited memory $\bar{m}_i$ and computation capacity $\bar{c}_i$, preventing it from performing the inference independently onboard. Such resource-constrained UAVs may delegate some subsequent inference tasks to the neighboring UAVs, in order to perform a complete classification locally.

We denote the 3D coordinates of each UAV $i \in \mathbb{N}_N$ by $(x_i, y_i, h_i)$ and we assume for simplicity that all UAVs fly at a fixed altitude above the ground, namely $h_i = H$, while considering the minimum $H$ value required for safety (e.g., building or structure avoidance) [37]. The horizontal coordinates $(x_i, y_i)$ of a UAV $i$ vary over time following the trajectory of the master node. In this way, each UAV deployed in the network moves from its initial position to the final destination in a cyclic trajectory to cover the target area. The positions of UAVs are recorded periodically at each $T$ time step. This means that the position of each UAV is repeated every $T$ seconds. Therefore, the optimization introduced in the next section is executed periodically to handle the network variation (connectivity and U2U link quality) and the dynamic incoming requests.

In this work, we consider a swarm of UAVs cooperating to execute a single CNN model, which means we are dealing with homogeneous input data acquired by these UAVs and requiring classification. Let $M$ define the number of layers characterizing the considered CNN model, in other terms, it defines the number of sub-tasks that should be distributed among the available UAVs and executed to perform the classification of the input data. Each layer of the CNN model is characterized by a memory requirement and a computation demand $c_i$. In
In this context, different UAVs are endowed with a copy of the trained model, allowing them to execute any assigned sub-task. Let $K_j, \forall \ j \in \{1, \ldots, M\}$, be the size of the intermediate output generated by layer $j$ and transmitted to the subsequent layer $j+1$ of the CNN model, and let $K_s$ denote the memory occupation of the input image acquired by the source node and requiring classification. This image is potentially transmitted to a neighboring UAV for the execution of the first layer. Furthermore, each UAV $i \in \{1, \ldots, N\}$ generates a number of requests $R_i$, such that $0 \leq R_i \leq R$.

As the G2U links are only used to offload the classification results in our scenario, our work will focus only on scheduling the U2U communication between different UAV participants to perform classification tasks. Specifically, a U2U link is established between any two UAVs $i$ and $k \in \mathbb{N}_N$, which are characterized by the estimated achievable data rate defined as follows \cite{38}:

$$\rho_{i,k} = B_i \log_2(1 + \Gamma_{i,k}),$$  \hspace{1cm} (1)

where $B_i$ denotes the bandwidth of the UAV device $i$ and $\Gamma_{i,k}$ is the average Signal-to-Interference-plus-Noise Ratio (SINR) of the U2U link between UAVs $i, k \in \mathbb{N}_N$.

Next, we will design an optimal placement of different layers in the UAV units participating in our distributed and collaborative system, while considering the resource capabilities of the devices. As previously described, the optimization is executed periodically to cover the variation of the network density and the UAVs location. We emphasize that the proposed distribution encompasses only standard CNN models with known types of processing (e.g., convolutional, ReLU, etc.), and without any residual block \cite{39}.

### B. Optimal UAV-based layer distribution (OULD)

In this section, we introduce the proposed methodology for the optimal placement of different classification sub-tasks incoming from data-generating UAV nodes, with an objective to minimize the total latency in decision making while considering only onboard UAVs. This latency is defined as the required time to transfer the output of layers between participants and to compute different tasks. We formally define the distribution problem as an optimization problem subject to the UAVs computation constraints. Our objective in this paper is to minimize the latency of classification tasks, which is the delay spent for executing different layers and the delay to communicate their intermediate data. The proposed strategy relies on 3D matrix of decision variables, namely $\alpha_{r,i,j}$, that returns 1 if the UAV $i$ executes the layer $j$ of the request $r$, and 0 otherwise:

$$\alpha_{r,i,j} = \begin{cases} 
1 & \text{if UAV } i \text{ executes the layer } j \text{ of request } r, \\
0 & \text{otherwise.} 
\end{cases}$$  \hspace{1cm} (2)

The objective function models the end-to-end latency spent to classify all incoming requests $R$ to the network composed of $N$ UAVs using collaborative inference. Such as the execution of each request is composed of $M$ subtask depending on the type of incoming request, knowing that a CNN model is composed of $M$ layers. The end-to-end latency (or decision-making latency) is defined as the time between gathering images of size $K_s$ by the source nodes and the decision-making. The objective function to be minimized is formulated as follows:

$$\min_{(\alpha_{r,i,j})} \sum_{r=1}^{R} \sum_{i=1}^{N} \sum_{j=1}^{M-1} \alpha_{r,i,j} \cdot \alpha_{r,k,j+1} \cdot \frac{K_j}{\rho_{i,k}} + t_s$$  \hspace{1cm} (3)

s.t

$$\forall i \in \mathbb{N}_N \sum_{r=1}^{R} \sum_{j=1}^{M} \alpha_{r,i,j} \cdot m_j \leq \bar{m}_i$$  \hspace{1cm} (4)

$$\forall i \in \mathbb{N}_N \sum_{r=1}^{R} \sum_{j=1}^{M} \alpha_{r,i,j} \cdot c_j \leq \bar{c}_i$$  \hspace{1cm} (5)

$$\forall r \in \mathbb{N}_R, \forall j \in \mathbb{N}_M \sum_{i=1}^{N} \alpha_{r,i,j} = 1$$  \hspace{1cm} (6)

$$\forall r \in \mathbb{N}_R, \forall i, j \in \mathbb{N}_M \alpha_{r,i,j} \in \{0, 1\}$$  \hspace{1cm} (7)

where

$$t_s = \sum_{r=1}^{R} \sum_{i=1}^{N} \sum_{k=1}^{N} \sum_{j=1}^{M-1} \mu_{r,i,k} \cdot \alpha_{r,i,j} \cdot \alpha_{r,k,j+1} \cdot \frac{K_s}{\rho_{i,k}}$$  \hspace{1cm} (8)

In the objective function \textcircled{3}, we define two different components of the latency:

1. The source latency $t_s$ defined in Eq. \textcircled{8}, which is the time required by the UAV source to transmit its gathered image to the UAV executing the first layer of this request. We remind that each UAV has a number of requests $R_i \in \mathbb{N}_R = \{0, \ldots, R\}$, such that $R = \sum_{i=1}^{n} R_i$, and $\bar{K}_r$ is the complement of the decision variable $\alpha_{r,i,j}$.

2. Time spent on transmission of the intermediate outputs between UAVs responsible of different tasks. More formally, the transmission time of the intermediate output of layer $j$ between UAVs $i$ to $k$ is given by $\frac{K_{r,j}}{\rho_{i,k}}$, where $\rho_{i,k}$ is the data rate of the U2U link between UAVs $i$ and $k$ and $K_j$ is the size of the generated output from layer $j$ of the CNN model.

The wireless communication is the key characteristic that distinguishes a UAV system from IoT or terrestrial ad-hoc networks, where the machine learning distribution is widely studied. The air-to-air communication channel is known by the high probability of line of sight that depends on the altitude of UAVs, which is not the case of terrestrial networks.

The constraint in Eq. \textcircled{4} ensures that each UAV executes multiple layers from multiple requests, while not exceeding its memory limit. Eq. \textcircled{5} guarantees that the constraint on computational load is respected for all participants, while assigning the classification tasks. The constraint in Eq. \textcircled{6} implies that each layer $j \in \mathbb{N}_M$ for each request $r \in \mathbb{N}_R$ is executed once in a single UAV. This constraint is designed to avoid redundant tasks execution. Finally, the constraint in \textcircled{7} ensures that the decision variable is binary and takes only a value of 0 or 1.
We can see that the objective function in the optimization problem (3) is nonlinear (NLP) and non-convex. More specifically, a problem that involves non-convex objective function/constraints may have multiple feasible regions and local optimal points, which makes solving it extremely complex and it may take exponential time in the number of variables and constraints to determine the global optimum across all regions. Therefore, in our work, we try to ensure the convexity and linearity of the optimization. More specifically, we introduce a new decision variable, namely $\gamma_{r,i,k,j}$, defined by:

$$\forall r \in \mathbb{N}_R, \forall i, k \in \mathbb{N}_N, \forall j \in \mathbb{N}_M \gamma_{r,i,k,j} = \alpha_{r,i,j} \alpha_{r,k,j+1},$$

(9)

where $\gamma_{r,i,k,j} \in \{0,1\}$ is the big M rule parameter used to convert the non-linear integer problem to linear, which is defined in our case as the transmission of the output of the layer $j$ computed in the UAV $i$ to the next participant $k$. Particularly:

$$\gamma_{r,i,k,j} = \begin{cases} 
1 & \text{if UAV } i \text{ executes the layer } j \text{ of request } r \text{ and sends the output to the UAV } k \text{ to compute the next layer } j + 1. \\
0 & \text{otherwise.} 
\end{cases}$$

(10)

To ensure that $\gamma_{r,i,k,j}$ is equal to $\alpha_{r,i,j} \alpha_{r,k,j+1}$, three constraints should be considered following the big M integer and linear programming rule [20]:

$$\forall r \in \mathbb{N}_R, \forall i, k \in \mathbb{N}_N, \forall j \in \mathbb{N}_M \gamma_{r,i,k,j} \leq \alpha_{r,i,j},$$

$$\gamma_{r,i,k,j} \leq \alpha_{r,k,j+1},$$

$$\gamma_{r,i,k,j} \geq \alpha_{r,i,j} + \alpha_{r,k,j+1} - 1.$$  

These constraints ensure that $\gamma_{r,i,k,j}$ is equal to 0, if $\alpha_{r,i,j}$ or $\alpha_{r,k,j+1}$ is null and equal to 1 if both of them are equal to 1. In this way, our new Integer Linear Programming (ILP) optimization will include two decision variables $\gamma_{r,i,k,j}$ and $\alpha_{r,i,j}$ and the objective will be reformulated to:

$$\min_{(\alpha_{r,i,j}, \gamma_{r,i,k,j})} \sum_{r=1}^R \sum_{i=1}^N \sum_{k=1}^N \sum_{j=1}^{M-1} \gamma_{r,i,k,j} \frac{K_j}{\rho_{i,k}} + t_s$$

(12)

where

$$t_s = \sum_{r=1}^R \sum_{i=1}^N \sum_{k=1}^N \mu_{i,r} \gamma_{r,i,k,1} \frac{K_x}{\rho_{i,k}}$$

(13)

Following the changes introduced to make our problem linear and convex, finding the optimal solution becomes less complex and less time consuming.

**C. OULD with mobility prediction (OULD-MP)**

The distribution approach described in the previous section gives efficient results for the homogeneous mobility model (Figure 2a), where the relative distance between UAVs remains static during the swarm movement in the target region. Such as figure 2 shows the positions of all UAVs at each time step $t$ for both scenarios homogeneous and non-homogeneous which are distinguished by the relative distance between the UAVs involved in the inference process. The use of OULD method in the non-homogeneous mobility scenario requires multiple runs for each network configuration while the swarm is moving through time. This increases the complexity of the optimization solution, gives a sub-optimal distribution policy, and introduces an additional delay in the decision-making latency. Thus, when the relative distance between UAVs changes, the OULD distribution policy does not present an efficient solution due to the change in data rate-based distance between UAVs. In this section, we tailor the proposed approach to cover the non-homogeneous mobility model (Figure 2b) in a one shot optimization, by considering a mobility prediction for the time steps $t \in \{1..T\}$ which consists of adopting a mobility model to predict the future locations of UAVs at each time step $t$. This allows us to perform a single distribution by solving the optimization problem, while considering the future locations of UAVs. This results in an optimal solution that is efficient for, not only the current time step, but also for some future ones. This helps us in avoiding to run the optimization problem each time step (knowing its complexity and the execution time) to handle data-rate variation between UAVs that tremendously influences the performance of the inference task distribution in terms of end-to-end latency. The mobility model plays a key role in the design of cooperative applications involving swarm of UAVs, such as crowd or region monitoring as well as critical platform surveillance. More precisely, the mobility model relies on different constraints, such as the energy constraint for path planning, area coverage, and network connectivity. The latter constraint has a substantial impact on our system since the loss of an intermediate task assigned to a disconnected UAV due to communication outage implies the loss of the inference of the corresponding request. In this paper, the distances,
connectivity, and movements of UAVs, as well as the swarm participants (e.g. joining and leaving devices) that depict the variation of the network at each time step are modeled through the communication link quality. Indeed, the link quality will be represented by the transmission data rate $\rho_{i,k}$ which denotes the expected amount of data transmitted between 2 UAVs $i$ and $k$ per movement period. More specifically, as shown in equation (1), one of the main factors affecting the physical data rate $\rho_{i,k}$ of a wireless link is the SINR ratio, which depends on the path loss. Because of this path loss, the received signal power is proportional to $d_{i,k}^{-\alpha}$, where $d_{i,k}$ is the distance between the transmitter $i$ and receiver $k$ and $\alpha$ is the path loss exponent. In this way, when $d_{i,k}$ is higher, the related data rate is lower. Meaning, lower data rates correspond to distant UAVs and vice-versa. Moreover, if the data rate between two UAVs becomes larger over time, it means that these devices are approaching each other. Finally, if the distance is very high and causes wireless link disconnection, the path loss and SINR can be approximated to 0 and $\rho_{i,k}$ will be accordingly equal to $B_i*log_2(1) = 0$. To summarize, the data rates characterising different participants can be used to define the distances between them, the possibility to perform data transmission, and their positions and movements over time.

Various mobility models are suggested in the literature to match different application requirements. In our work, we will adopt the Reference Point Group (RPG) mobility model introduced in [40], which is the most suitable model for target region surveillance and fits our intention of distributing inference tasks among a set of UAVs. More specifically, this mobility model is designed to manage the behavior of the swarm that needs to follow a logical center or the group leader. All the UAVs in this group are randomly distributed around the reference node and combine their own mobility models with that of the group leader, which makes them follow the direction of the group, with a small range of liberty. In the RPG model, the group leader follows a round trip movement between an initial and a final point, chosen in such a way to cover the entire target area. The movement of the leader UAV defines not only its motion but also the motion trend of all UAVs inside the group. Otherwise, UAVs within the group can deviate from the planned path and lose the global motion trend, even if they are still in the group range. To enhance our static distribution methodology, we will consider the predicted locations of all UAVs in the network, at each time step for a time duration $T$. The same decision variables $\alpha_{r,i,j}$ and $\gamma_{r,i,k,j}$, defined in Eq.(1) and Eq. (10) respectively, will be used in this section, since the objective remains the same and the extension of the model resides only in finding an adaptive distribution of the CNN tasks between a moving set of UAVs for a certain time duration. In other words, $\alpha_{r,i,j}$ and $\gamma_{r,i,k,j}$ in this case present the inference task $j$ of the request $r$ assigned to UAV $i$ and the transmission of the $j$ layer output between two devices during a period of time $T$. Hence, the objective function defined in Eq.(12) is reformulated as follows:

$$\min_{(\alpha_{r,i,j}, \gamma_{r,i,k,j})} \sum_{t=1}^{T} \sum_{i=1}^{R} \sum_{k=1}^{N} \sum_{j=1}^{M-1} \gamma_{r,i,k,j} - \frac{K_j}{\rho_{i,k}(t)} + t_s \tag{14}$$

where

$$t_s = \sum_{r=1}^{R} \sum_{i=1}^{N} \sum_{k=1}^{N} \mu_{i,r} \gamma_{r,i,k,1} \frac{K_s}{\rho_{i,k}(t)} \tag{15}$$

The problem constraints defined in Eq.(5), (4), and (6) will not be reformulated, as the UAVs’ mobility model during the mission does not impact the memory occupancy and the computation capability. These constraints depend only on the distribution map $\alpha_{r,i,j}$, the capacities of devices and the resource requirements of different layers. The objective function defined in Eq.(14) is composed of two latencies. The first part presents the time spent to transmit the intermediate outputs while considering the movement of UAVs during the time steps $t \in \{1..T\}$. This mobility results in a data rate variation while transmitting the layers outputs between any two UAVs $i$ and $k$, which is presented by $\rho_{i,k}(t)$. Thus, the variation of the relative distance between UAVs during swarm mobility influences the intra-communication quality, consequently impacts the end-to-end latency through intermediate outputs transmission.

IV. PERFORMANCE EVALUATION

In this section, we evaluate the performance of our distribution methods under different configurations of the UAV network (e.g. capabilities of the UAVs, trained CNN network, covered area, etc.). The proposed methodology has been simulated by solving the optimization problem defined in Eq. (3) and (14). Due to the complexity of our combinatorial optimization solution, we used an High Performance Computer
consider two levels of memory capabilities; a high-level technological Raspberry Pi micro-computer families [43], where the performance of our distribution strategy on different memory and computation constraints is examined. We evaluate UA Vs to accomplish the distributed inference.

presented in our work as the shared data exchanged between inference and are evaluated in general based on the decision-time. Indeed, these surveillance systems that require real-time are communicating with each other to ensure collaborative inference using the bandwidth $B_i = 20$ MHz. As the CNN depth has a great impact on the number of requests that can be classified by leveraging the available resources, we are examining throughout this simulation the performance of our system on two CNN models; namely Lenet composed of 7 layers and VGG-16 [19] that comprises 18 layers. We adopt in our system a pedestrians surveillance scenario, where we classify 595x326 RGB images from the Stanford Drone Dataset [42]. The memory requirements per layer of each CNN model to infer one image are shown in Figure 3. These footprints of different layers are calculated using Keras in Google collab. The Figure shows that the memory demand of the CNN model including that of the input, intermediate, and output data as well as the size of millions of parameters (weight and biased) may prevent it from being executed on a single UAV.

A. OUD evaluation

In this section, we conduct a distribution of classification requests on a homogeneous network mobility, where the UAVs' relative distance remain static over traveling time, as presented in section III-B. We emphasize that a key advantage of our approach is that it does not impact the accuracy of the model during the distribution process. Indeed, our strategy guarantees the connection between UAVs participating in the distribution, so that the CNN model parameters are not distorted as intermediate data losses are not allowed. In this simulation, we are considering multiple CNN models distribution for an online system where dynamic incoming load requires real-time inferences. We concentrate our efforts on exploring the impact of our proposed method on the average latency per request and the shared data to study the efficiency of the obtained distribution policy on the performance of UAVs-based surveillance systems. While there are many parameters of importance, these two are critical to highlight in our work due to these surveillance systems that require real-time inference and are evaluated in general based on the decision-making latency as well as the cost of this process which is presented in our work as the shared data exchanged between UAVs to accomplish the distributed inference.

Figure 4 illustrates the distribution of Lenet incoming requests over a network of 10 UAVs, where the impact of memory and computation constraints is examined. We evaluate the performance of our distribution strategy on different technological Raspberry Pi micro-computer families [43], where we consider two levels of memory capabilities; a high-level memory equal to 512 MB and a low-level memory equal to 256 MB. Moreover, due to the static impact of the computation capacity, we are considering one computation level equal to 9.5 GFLOPS.

The solid green line in Figure 4a illustrates the optimal communication latency per request of a system that comprises 10 UAVs with high memory, deployed within a target area dimension equal to 100x100 m. The plot shape shows that this swarm of devices can cooperate to parallelize the classification of up to 18 requests. However, when the number of online incoming requests is high, the latency increases due to the increase of the intermediate exchanged data. In fact, the communication delay to transmit intermediate data generated by different layers dominates the computation latency (dashed green line) compared to the low computation requirements of the Lenet model. Accordingly, when the load of requests is low, several Lenet classifications can be processed by a single device without the need for distribution as depicted by the green solid line. Meanwhile, when the online load is high and the memory capacity will not able to handle all requests locally and the system starts to resort to the distribution even when the network is small, e.g. Lenet. Similarly, the communication latency increases with the increase of the incoming load, which is explained by the high intermediate data exchange between UAVs and the interferences occurring between participants. The simulation results presented by the blue line is conducted in a network of UAVs characterized by low memory - high computation level. The overall latency of this simulation increases significantly compared to the previous configuration presented by the green line; this is due to the limited memory that restricts the system capacity while increasing the overall latency. The system capacity is defined by the ability of the network to handle a maximum number of parallel classification requests.

The yellow line in the Figure 4a illustrates the optimal latency per request for a network of 15 UAVs deployed in the same target area dimension of 100x100 m where the UAVs are equipped with high memory. We can see that increasing the number of participants contributes to enhance the system capacity. More specifically, the system can handle up to 14 Lenet requests processed autonomously, compared to 10 requests classified locally when involving 10 participants (the green line). Therefore, for the lower loads, only the computation delay impacts the total latency, whereas the communication delay added for distribution dominates the classification time, when the load is high. To summarize, a higher network density contributes to enhance the system capacity to deal with simultaneous classification requests (18 requests when 10 UAVs participate in the collaborative system and 25 when involving 15 devices.). However, when the number of participants is higher, the overall latency increases significantly, which can be explained by the additional overhead resulting from the interference occurring in a dense network as considered in our data rate model (Equation 1) based on [38].

Figure 4b depicts the amount of data exchanged between UAVs to perform distributed inferences following the scenarios simulated in Figure 4a. We can see that a network with low memory UAVs requires high data exchange. This is related to
Fig. 4: Performance evaluation of our proposed distribution method, namely OULD, while varying the network density $N$ and the memory capability $m$. Two parameters are studied: the average latency per request and the shared data transmitted between the involved UA Vs in the cooperative inference.

Fig. 5: Optimal decision-making latency of a distributed VGG’s inference over a network of 10 UA Vs.

Fig. 6: Optimal decision-making latency of a distributed VGG’s inference over a network of 15 UA Vs.

the incapacity to accomplish autonomous classifications and the need to resort to distribution. Meanwhile, a higher network density combined with high memory capabilities contributes to increase significantly the system capacity to compute more layers in a single device and minimize the data sharing. The yellow dotted line depicts the shared data for a network of 15 UA Vs with low memory constraints, such as a large amount of data is exchanged in this network to process cooperatively the 12 incoming requests which is the system capacity as shown by the red line in Figure . This is due to more resource-constrained UA Vs are involved in the cooperation process which increases the system capacity by 2 requests compared to the blue dashed line that depicts results for a network of 10 UA Vs. After reaching the system capacity the additional incoming request will not be handled in parallel which results in stable shared data as we can see for the green line after 18 requests (as shown by green line in Figure 4a).

Figures 5 and 6 present the performance of our system when receiving requests for classification using VGG-16 network, which is considered as one of the most complex and deep CNN models. Unlike the Lenet model where some requests may be handled locally without distribution, the VGG-16 requires collaborative inference because of its high memory and computation demand. Figure 5 shows the performance of a network composed of 10 UAVs with different memory constraints. When the UAVs are endowed with high memory and computation levels (see Figure 5a), we can notice that the computation highly dominates in the end-to-end latency.

Figure 6 illustrates the distribution of classification requests over a network composed of 15 UAVs. We can see in Figure 5b that when the UAVs have low memory constraints, the communication latency dominates the end-to-end latency.
that the optimal latency to process inferences on UAVs with high memory increases when the incoming load is high. When the system reaches its maximum capacity (10 requests), the optimal latency increases tremendously dominated by the communication delay. This huge increase in the communication delay is resulting from involving all the UAVs including the devices with the worse location, which disturbs the overall communication in the network by creating interferences. This scenario is not faced when the number of participants is equal to 10 (see Figure 5), due to the small network density and low probability of interference. Otherwise, when the system reaches its maximum capacity, the communication delay becomes greater due to the network density and the interferences created by the low-performance nodes, disturbing the transmission. The performance of our approach when deploying low memory UAV devices is shown in Figure 6b. We can see that the system capacity to handle online incoming requests is reduced compared to the previous configuration depicted in Figure 6a, which illustrates again the importance of the memory level endowed with devices in maximizing the number of simultaneous classifications. We also emphasize that the impact of the network density on the end-to-end latency in terms of interference is reduced due to the low number of computed requests. Figure 7 depicts the amount of data exchanged between UAVs to perform distribution following the scenarios simulated in Figures 5 and 6. In addition to the high computation requirements of VGG-16, we can see that the exchanged data to conduct the cooperative inference is greater than Lenet, which justifies its high inference latency per request. Unlike Lenet, the VGG-16 system deploying UAVs with high memory level exchanges more data than the one using low memory devices due to its capacity to handle a higher number of requests. The maximum number of VGG requests that can be handled onboard the UAV swarm is smaller compared to Lenet which are respectively 10 and 25 requests, this is due to the high memory and computation requirements of VGG. So as a system deploying a low number of UAVs equipped with low memory capacity achieves low capacity such after only 3 incoming requests start rejecting requests that result in stable shared data as seen for the blue line.

In Figure 8, we show the performance comparison of our OULD method and three heuristic schemes designed to distribute the inference task between UAVs for a single configuration obtained from a fixed time step. In the Nearest heuristic method, the nodes that receive the computing task search among its neighbors the nearest one with enough memory to process the remaining layers. Regarding the High Residual Memory heuristic (HRM), the node selects the UAV in its neighborhood with highest residual memory. The third heuristic combines both the nearest and HRM, where the UAVs requiring cooperation select the nearest UAVs with high residual memory to participate in the cooperative inference. In Figure 8a, we plot the incoming request in terms of average latency per request for all methods. We can see that our optimization solution outperforms the heuristic methods.
Otherwise, the heuristic method selecting the nearest nodes to transmit its intermediate output performs well compared to the two other heuristic methods. This can be explained by the fact that the nearest nodes possess high data rate links which result in lower average latency per request compared to the method based on memory constraints. Meaning, air-to-air communication has a great impact to determine the optimal distribution policy.

### B. OUD-MP evaluation

In this section, we focus on evaluating the performance of the proposed methodology in section II-C where we take into consideration the mobility model adopted by the UAVs that describe their movement during the mission and is defined by different locations of UAVs at each point of time. Indeed, since the locations of all UAVs are known during a period of time, we discretize this duration into time steps; each one indicates the new positions of the moving UAVs. In this way, a single distribution policy is adopted during this interval of time; which enhances the delay performance of the proposed approach by preventing the execution of the optimization problem for each topology variation. Furthermore, solving a one-shot optimization presents an optimal distribution policy, since the system selects UAVs performing different tasks while considering their future locations to ensure the non-disconnection between devices; and consequently guarantee the completeness of the whole classification and the accuracy of the model. This is not the case of the static network configuration, where we execute the optimization for each variation of the system and decisions do not consider possible disconnections or data rate decrease.

Figure 9 presents the optimal decision-making latency of a distributed Lenet’s inference over a network of UAVs deployed $100^2 m$ area using mobility prediction.

![Fig. 9: Optimal decision-making latency of a distributed Lenet’s inference over a network of UAVs deployed $100^2 m$ area using mobility prediction.](image)

(b) $m = 512$ MB and $c = 9.5$ GF

(a) $m = 512$ MB and $c = 9.5$ GF

(b) $m = 256$ MB and $c = 9.5$ GF

Fig. 9: Optimal decision-making latency of a distributed Lenet’s inference over a network of UAVs deployed $100^2 m$ area using mobility prediction.

The optimal decision-making latency of a UAV network deployed on a target area of $500^2 m$ is presented in Figure 10, where different UAVs properties are examined. Figure 10a shows the performance of a network with a low memory capacity, which means a higher requirement for distribution and consequently a huge data exchange between participants. Particularly, the intermediate output transmission introduces a significant communication delay to the end-to-end latency; which makes the computation delay of such a small model negligible compared to the communication overhead.

![Fig. 10: Optimal decision-making latency of a distributed Lenet’s inference over a network of UAVs deployed $500^2 m$ area using mobility prediction.](image)

(b) $m = 256$ MB and $c = 9.5$ GF

(a) $m = 512$ MB and $c = 9.5$ GF

Fig. 10: Optimal decision-making latency of a distributed Lenet’s inference over a network of UAVs deployed $500^2 m$ area using mobility prediction.

Unlike the previous network configuration evaluated in Figure 2a, a single distribution policy cannot be found for multiple time steps due to the wide target area resulting in a high topology variation, which increases the impact on the inference time. In addition, we can notice a lower overall latency compared to the same network deployed in a $100^2 m$ area and evaluated in Figure 9a. This can be explained by the low interference between UAVs, as they are deployed in...
Fig. 11: Optimal decision-making latency of a distributed VGG’s inference over a network of UAVs deployed 100\textsuperscript{2}m area using mobility prediction.

(a) \( m = 512 \) MB and \( c = 9.5 \) GF

(b) \( m = 256 \) MB and \( c = 9.5 \) GF

Fig. 12: Optimal decision-making latency of a distributed VGG’s inference over a network of UAVs deployed 500\textsuperscript{2}m area using mobility prediction.

(a) \( m = 512 \) MB and \( c = 9.5 \) GF

(b) \( m = 256 \) MB and \( c = 9.5 \) GF

Fig. 13: Performance comparison of our proposed method OULD-MP using mobility prediction and the offline distribution designed in [32].

(a) Latency in function of incoming requests

(b) Latency in function of incoming requests

Figures [11] and [12] depict the optimal decision-making latency when distributing VGG-16 inferences over UAVs deployed respectively in 100\textsuperscript{2} m and 500\textsuperscript{2} m areas. The performance of the network composed of UAVs characterized by a high memory capability is shown in Figure [11a]. This Figure shows that the overall latency increases over time steps as different policies are required for each mobility prediction duration. In this scenario, the overall latency increases over time to handle multiple topology variations. We note that adopting single policy as done for Lenet cannot be applied for VGG due to its large depth and the low memory capacity of the deployed UAVs. Figure [12] shows the performance of a network of UAVs deployed in a target area of 500 \textsuperscript{2}m. In Figure [12a], we can clearly notice that the computation time hugely dominates the overall latency when the UAVs are equipped with high memory capability. Meaning, an efficient inference distribution is designed, particularly for low mobility prediction duration, since the overall latency is spent on computation in addition to high distribution demand due to resource-constrained UAVs.

In Figure [13] we show the performance comparison of our proposed method OULD-MP that uses the mobility prediction and the reference method in [32], where the offline distribution of multiple models is suggested. In Figure [13a], our OULD-MP shows stable average latency per request during the 10-time
steps where the UAVs are moving in the targeted region. This is due to the mobility prediction used in our proposed method to ensure optimal distribution for a bounded duration of time. The method of [32] shows good results for the first 5 time slots compared to OULD-MP since the optimal policy deployed does not take into consideration the new location of UAVs, such as the involved nodes in the distribution are moving away from each other, which results in an outage of communication in time step 7. Consequently, the incoming requests can not be processed collaboratively and may be rejected.

C. Complexity analysis

The computational complexity of an optimization problem depends, in general, on the problem formulation and the technique that is used for solving it. In some algorithms, the complexity can be measured by the time that the CPU needs to run the algorithm, others approximate the computational complexity by the number of constraints and the nested loops in the objective function per run, which can be written as $O(\cdot)$. In both approaches proposed, we have the same constraints. The difference resides in the objective functions, whose complexity is equal to $O(RN^2(M-1))$ for the static configuration OULD and $O(TRN^2(M-1))$ for OULD-MP. However, when dealing with the static configuration, the optimization needs to be re-run for each network change (e.g. topology variation, new incoming requests, disconnection of UAVs, etc.). Hence, the runtime of a single problem needs to be multiplied by $T$ that denotes the number of time slots where the system changes. Meanwhile, OULD-MP is a one shot optimization. On these basis, comparing both problems’ runtime complexity is not straightforward. Therefore, we measured the time that the CPU requires to run the two approaches, following the same parameters. Figure 14 presents a comparison between OULD and OULD-MP in terms of runtime, for different loads of concurrent requests and when increasing the number of time steps. We can see that for different configurations, OULD-MP covering the mobility of devices presents a lower runtime than OULD approach, where we need to run the simulation each time the network changes. Hence, the mobility study adds not only an overview about the status of the system in the next time slots to avoid any disconnection scenario and establish transmissions between devices with expected higher data rates, but also presents less complexity and better runtime.

D. Results Summary

We used in our simulation Lenet and VGG-16 due to their different complexities and computation requirements in order to study the tradeoff between the number of requests that could be processed in parallel, the number of UAVs available to perform collaborative inference as well as their computation capabilities. In addition, we considered the impact of the wireless communication between the UAVs on the end-to-end latency through a data rate model from [38] including the interferences that occur in the network. Although multiple parameters such as air traffic control, climb rate, reliability were not covered in this study, we decided to cover two critical parameters (average latency and shared data) due to the characteristics of our UAVs system. This later is composed of a set of UAVs deployed in the targeted area for surveillance purposes such as all the UAVs coordinate their movement following the reference point mobility model in order to cover the target surface.

As shown in our study, some UAVs with limited computation and memory capabilities are not able to process an entire request of high complexity as VGG-16 or multiple incoming simple requests as Lenet. Our OULD method showed efficient results to process collaboratively multiple incoming requests whatever their type is instead of using a server to remotely process the collected data. The use of a server introduces multiple drawbacks, especially for online systems that require real-time processing, such as the high latency spent on communicating the data to the server and the complex deployment of the system. Furthermore, When the mobility model followed by the UAVs participating in the collaborative inference process is non-homogeneous, the link quality between UAVs will change or can eventually be lost. For this reason, our OULD method should be executed each time step for each network configuration, which makes it impractical, non optimal on overall throughout all time steps and introducing a computational complexity to the optimization. To solve this issue, we proposed the use of mobility prediction (ML-OULD) where the positions of all UAVs are known for some time steps that allow performing distribution, while taking into consideration the future positions of UAVs and avoiding periodic execution of OULD method. As a result, our ML-CLUD method showed efficient performance in terms of decision making latency while considering time variation of the wireless channel between the UAVs.

V. CONCLUSION

A distributed CNN inference method is proposed in this paper in order to fit the CNN memory requirements to the resource-constrained UAVs and allow performing on-site
classification instead of delegating the decision-making to a server. The distribution scheme in this paper is formulated as an optimization problem, where the objective function consists of minimizing the decision-making latency. In addition, the mobility model followed by the UAVs and their varying topology are well studied in our optimization due to its impact on the decision-making latency.

Furthermore, a mobility prediction is considered in the tailored model to prevent multiple executions of the optimization problem for each topology variation. Our simulation unveiled different parameters that should be present to achieve an efficient distribution of CNNs, including the density of UAVs, their capacities, and the mobility model. However, the optimization is characterized by its complexity, which makes finding the optimal solution extremely challenging. For this reason, we plan in future works to use reinforcement learning as an alternative to the optimization as it showed a high capacity to pursue the optimal solution in resource allocation scenarios.

REFERENCES

[1] P. Lottes, R. Khanna, J. Pfeifer, R. Siegwart, and C. Stachniss, “Uav-based crop and weed classification for smart farming,” in 2017 IEEE International Conference on Robotics and Automation (ICRA), 2017, pp. 3024–3031.
[2] S. Sawadisatang, D. Niyato, P. Tan, and P. Wang, “Joint ground and aerial package delivery services: A stochastic optimization approach,” IEEE Transactions on Intelligent Transportation Systems, vol. 20, no. 6, pp. 2241–2254, 2019.
[3] K. Anderson and K. J. Gaston, “Lightweight unmanned aerial vehicles will revolutionize spatial ecology,” Frontiers in Ecology and the Environment, vol. 11, no. 3, pp. 138–146, 2013.
[4] F. Qi, X. Zhu, G. Mang, M. Kadoch, and W. Li, “Uav network and iot in the sky for future smart cities,” IEEE Network, vol. 33, no. 2, pp. 96–101, 2019.
[5] H. Dang-Ngoc and H. Nguyen-Trung, “Aerial forest fire surveillance - evaluation of forest fire detection model using aerial videos,” in 2019 International Conference on Advanced Technologies for Communications (ATC), 2019, pp. 142–148.
[6] J.-C. Padró, F.-J. Muñoz, J. Planas, and X. Pons, “Comparison of four uav georeferencing methods for environmental monitoring purposes focusing on the combined use with airborne and satellite remote sensing platforms,” International Journal of Applied Earth Observation and Geoinformation, vol. 75, pp. 130 – 140, 2019. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0303243418306421
[7] H. Kim, L. Mokdad, and J. Ben-Othman, “Designing uav surveillance frameworks for smart city and extensive ocean with differential perspectives,” IEEE Communications Magazine, vol. 56, no. 4, pp. 98–104, 2018.
[8] J. Gu, T. Su, Q. Wang, X. Du, and M. Guizani, “Multiple moving targets surveillance based on a cooperative network for multi-uav,” IEEE Communications Magazine, vol. 56, no. 4, pp. 82–89, 2018.
[9] A. Shamshooshara, M. Khaledi, F. Aghaf, A. Razi, and J. Ashdown, “Distributed cooperative spectrum sharing in uav networks using multi-agent reinforcement learning,” in 2019 16th IEEE Annual Consumer Communications Networking Conference (CCNC), 2019, pp. 1–6.
[10] L. Bashmal and Y. Bazi, “Learning robust deep features for efficient classification of uav imagery,” in 2018 1st International Conference on Computer Applications Information Security (ICCAIS), 2018, pp. 1–4.
[11] C. Kyrkou, G. Plastiras, T. Theocharides, S. I. Venieris, and C. Bougias, “Dronet: Efficient convolutional neural network detector for real-time uav applications,” in 2018 Design, Automation Test in Europe Conference Exhibition (DATE), 2018, pp. 967–972.
[12] C. Wang, J. Wang, Y. Shen, and X. Zhang, “Autonomous Navigation of UAVs in Large-Scale Complex Environments: A Deep Reinforcement Learning Approach,” IEEE Transactions on Vehicular Technology, vol. 68, no. 3, pp. 2124–2136, mar 2019.
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