Towards Enabling Unmanned Aerial Vehicles as a Service for Heterogeneous Applications

Farid Nait-Abdesselam, Ahmad Alsharoa, Mohamed Y. Selim, Daji Qiao, and Ahmed E. Kamal

Abstract: **The increasing use of unmanned aerial vehicles (UAVs) in various commercial applications, such as precision agriculture and aerial remote sensing, is fast contributing to a significant growth in the UAV market. Also, it is crucial to provide continuous coverage after failures of wireless network components or additional bandwidth in high traffic situations. By introducing the concept of UAVs as a service (UaaS), we propose a novel framework, dubbed D^3S, consisting of four phases:** *Demand*, *decision*, *deployment*, **and** *service*. **The main objective of this framework is to provide a realistic and streamlined approach to support the implementation of the UaaS paradigm. The technical problems involved include determining the type and number of UAVs to be deployed and their final locations (e.g., hovering or on-ground). They also include the trajectory planning, possibly several times, between charging stations and deployment locations. We present the application of the D^3S framework to two case studies with the goal of providing wireless connectivity services to (i) static users after failures of wireless network components, including long-term and short-term failures, and (ii) dynamic users in wireless relaying systems.**

Index Terms: **UAVs as a service (UaaS), unmanned aerial vehicles (UAVs), wireless networks.**

I. INTRODUCTION

UNMANNED aerial vehicles (UAVs) have been mainly used in military domains for years. More recently, UAVs have found many other civilian applications and their number is expected to grow very fast in the future. Recently, with their integration in our society, UAVs have found many civilian applications and the number and type of such applications are expected to grow fast in the future. The U.S. federal aviation administration (FAA) expects that UAVs will introduce a new paradigm shift and that they will do to aviation what the Internet did to information [1]. In the area of Information and Communication Technology, UAVs are gaining huge popularity mainly because of their ability to be equipped with communication and computational capabilities, as well as being highly scalable for on-demand deployment. In this regard, several well-known companies have launched pilot projects intending to provide *connectivity from the sky*, such as Odysseus project [2], Astigan project [3], and Zephyr project [4], which aim to leverage UAVs for providing worldwide access to the Internet. The 3rd generation partnership project (3GPP) is also looking at having UAVs supported by long term evolution (LTE) [5]. Also, with the approval of the FAA, AT&T and Qualcomm have already optimized their LTE networks for UAV communications [6], paving the way for deployments of UAVs in 5G networks. Extensive research efforts are also devoted to including UAVs in different wireless communication platforms [7], using them as aerial mobile base stations (BSs) [8] and mobile relays [9]. For example, project CAPANINA studied antennas to deliver broadband wireless access using UAVs [10]. Project ABSOLUTE aimed to design and implement LTE-A aerial base stations to provide wireless coverage for public safety usage during large-scale unexpected and temporary events [11].

All these innovative efforts are paving the way for a generic notion of UAVs as a service (UaaS), where a variety of UAVs-based applications could be developed. Open, standardized, and flexible UAV-based application development platforms are therefore needed in order to enable stakeholders to explore techno-economic boundaries and tradeoffs in the UAV ecosystem. Further, innovation in UAV applications requires such a UaaS vision to become a reality as a framework for developers and designers. A key challenge towards this vision of UaaS is the communication and networking capability of UAVs. Seamless and immersive solutions are therefore necessary to make many different UAVs work together without causing harm to humans while providing connectivity from the sky.

In this paper, we propose a framework to implement UaaS in order to provide an *end-to-end connectivity service* to applications such as the above. We refer to this framework as D^3S which is an acronym of the four phases of the framework: *Demand*, *decision*, *deployment*, and *service*. The main objective of this framework is to develop efficient and realistic solutions to support the UaaS paradigm. We present the four phases of the D^3S framework, and explain the methodologies used to implement them. We also present two case studies of the application of D^3S, where in the first one the focus is on using UAVs for mitigating the effect of cellular networks after component failures, and in the second one UAVs are used to provide connectivity between mobile users and a sink.

As an example of an application that uses UaaS, we consider the occurrence of a natural disaster, such as a hurricane, that damages the communication infrastructure in a certain area, e.g., a city. In 2017 several such hurricanes hit different parts of the U.S. such as Hurricanes Maria, Irma, and Harvey which damaged significant proportions of the wireless cell towers in several parts of Puerto Rico, Florida, and Southern Texas, re-

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spectively. For example, during Hurricane Harvey in Houston, all 911 call centers were damaged and 20 out of 27 cell towers covering the metropolitan Houston area were damaged. Trapped and stranded citizens, as well as rescue personnel, therefore cannot communicate with each other or with entities outside the disaster area. City officials can request communications services based on a demand that they estimate, in terms of bandwidth requirements and locations. A swarm of UAVs, equipped with wireless communications access points or base stations, can be deployed to provide the wireless communications services. The demands are used to determine the required number of UAVs, their 3D deployment locations and the communications capacities of the UAVs that will be needed to provide the required level of service, with a minimum cost. Another tier of UAVs may be needed to implement backbone connectivity between the UAVs, and between the UAVs and the core network. The UAVs need to be deployed, possibly from multiple locations, and the trajectories of flying from these locations to their final deployment locations are determined in order to minimize flying time, energy consumption and cost. After deploying the UAVs, association and communication between ground users and the UAVs, communication and routing between the UAVs, and between the UAVs and the edge access points to the core networks will have to be decided optimally and in a reliable manner. In this case, UAVs deployment can be implemented in two stages:

1. A short-term deployment stage of agile, albeit limited life time, UAVs, such as drones, in order to provide a minimum necessary level of service. Several drones may have to serve the same location due to their limited battery capacities, and the drones will have to commute between the service locations and the charging stations.
2. Then, a stage of long-term deployment of UAVs, such as helikites and balloons, which are more energy efficient but take longer to deploy. Once the second set of UAVs are deployed, the drones may be sent back to their charging locations.

This paper starts by introducing the D^3S framework for UaaS and its four phases. Then, each of the phases of the framework is described in detail. Two case studies of the application of the proposed D^3S framework are then presented, namely, UaaS for wireless networks self-healing and UaaS for connectivity of dynamic ground users. This will be followed by a short conclusion section.

II. THE D^3S FRAMEWORK FOR UAAS

In this section, we present the proposed framework for implementing UaaS. This framework consists mainly of four phases, *Demand*, *Decision*, *Deployment*, and *Service*, abbreviated as D^3S. The rationale for using four phases is to simplify and streamline the flow of processing in the framework, including the formal definition of feedback and feed-forward points in the framework, as shown in Fig. 1. The reason for this separation is also motivated by the possibility of working independently to optimize and improve each of the phases. The techniques and algorithms of each phase may therefore updated, replaced or fine tuned independently.

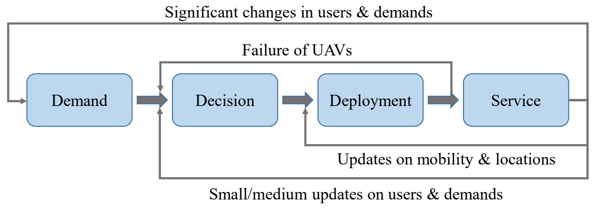

Fig. 1. The D^3S framework for implementing UaaS.

***Demand*:** In this phase, the entity requesting service places a request with a set of high-level parameters that characterize the requested service. These will include: (1) Type of request (disaster recovery, self-healing, etc.), (2) the location coordinates of the event and its coverage area, (3) the bandwidth required, (4) mobility characteristics of users, if any, (5) the computing power needed from the UAV, if any, (6) sensing services needed and sensing resolutions, and (7) the time frame of the requested coverage service.

Some of the demand parameters will not be deterministically available, e.g., in disaster areas. These will be learned by the system after deploying initial sets of UAVs, and have them collect information from ground users in order to estimate the demand parameters. This information will be used to revise the demand to be used in other phases. Finally, the specification of the demand will serve as an entry to the second phase, namely, the *Decision* phase.

***Decision*:** Based on requests made in the *Demand* phase, this phase will determine the types of UAVs to deploy, their optimal number, their precise deployment locations, and the bandwidth to be used by their communication components. The UAVs will therefore form a mesh network that will provide the requested service to a set of stationary, and/or possibly mobile, ground devices. As different types of UAVs and different deployment locations (e.g., hovering versus on-ground) may offer different tradeoffs in terms of energy consumption, flying time before the need to be recharged, size of the coverage area, etc, will be taken into consideration when making the decision. In addition, other mobile devices or devices that do not need continuous service, such as sensors in a farming field, will also be taken into consideration and linked to the determination of the trajectories taken by UAVs in the *Deployment* phase.

***Deployment*:** Once the types, numbers, and future locations of the UAVs are determined in the *Decision* phase, this phase will deal with defining the best trajectories of the UAVs to be deployed. The UAVs will be dispatched either from the same location, and therefore will be flying as a swarm towards the deployment location, or from different locations, therefore will fly individually and be gathered one-by-one to converge towards their deployment location. Multiple configurations to route these UAVs will be taken into consideration such that the energy resource will be used optimally.

***Service*:** In this phase, the proper coverage service to achieve end-to-end connectivity will be provided. This includes communication of UAVs with ground users (stationary or mobile), routing of data between UAVs, and routing of data to and from access points to the core network.

Short-Term versus Long-Term Service: Two time scales will be used to provide service: **short-** and **long-term**. The short-term service provisioning refers to the use of UAVs that can be deployed with agility, e.g., drones. These UAVs typically have short flying and hovering times but can be deployed to provide service with a very short delay. The long-term service provisioning uses UAVs that take longer to deploy but can stay in service for a long time without requiring maintenance or recharging, e.g., helikites, airships, and balloons. The use of short-term followed by long-term, short-term only, or long-term only, depends on the application and the application domain and its properties. For example, disaster recovery and self-healing of wireless systems can use short-term followed by long-term service. For applications involving forecasted increase in bandwidth demand, such as in football games, pre-planning can be implemented ahead of the event and long-term service can be provisioned. The introduction of these two time scales, and the transitioning between them will be implemented by the Decision, Deployment, and Service phases of the framework. Fig. 2 shows an example of the application of four phases of the D^3S framework. As shown in the figure, the demand phase receives demands from different sources, processes them, then the output of this phase is forwarded to the decision phase which will make decisions related to the amount of bandwidth needed, the types and number of UAVs. After that, the output of the decision phase will be fed to the deployment and service phases. A disaster scenario is considered where the cellular service is assumed to be out of service and the UAVs are going to provide temporary cellular service to the first responders as well as the users stuck in the disaster area.

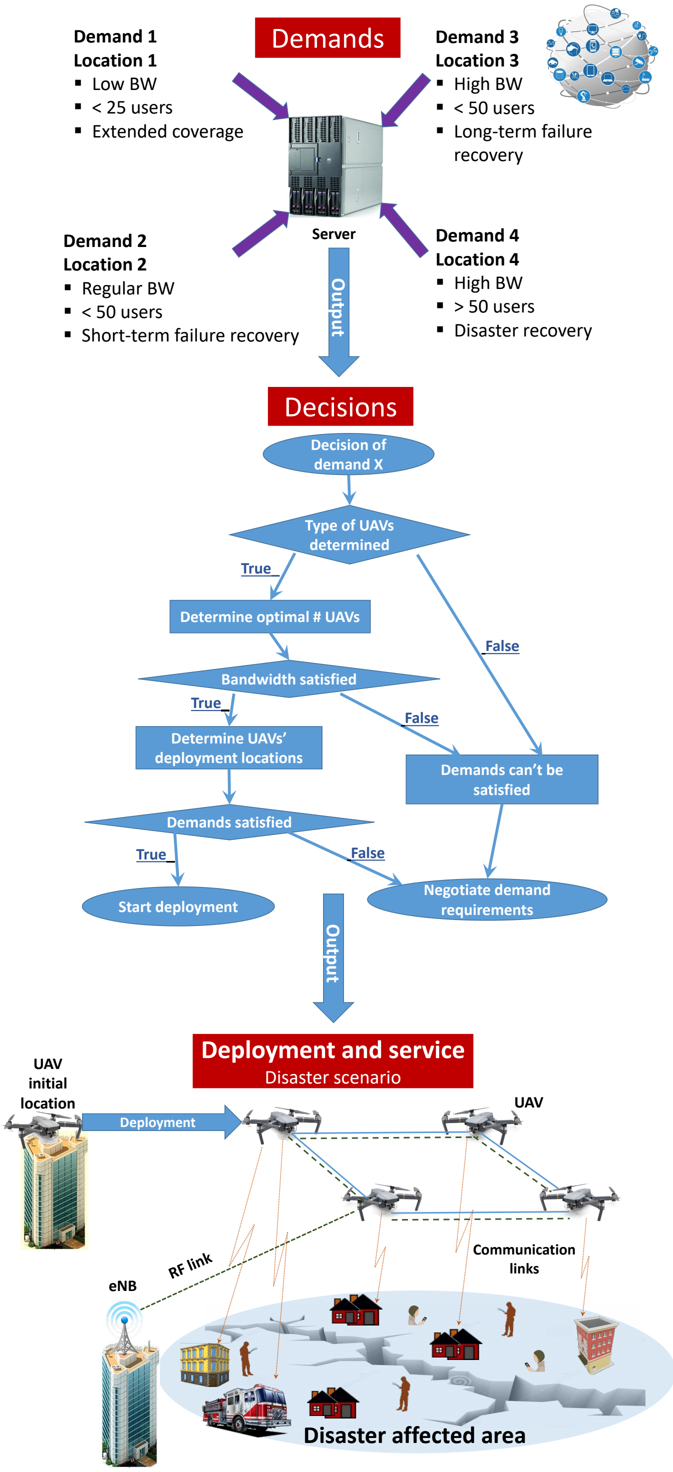

Fig. 2. The D^3S Phases: Demand, Decision, Deployment, and Service.

III. DEMAND FORECASTING AND CHARACTERIZATION

In the first phase of the framework, the entity requesting a service must provide information about the type of service (e.g., disaster recovery), the devices to be served, whether they are stationary or mobile, and the requested service rates. The requested service duration can also be identified, and whether the service is continuous or intermittent, e.g., for sensors. The information may also be updated with time (Fig. 2).

This information can be provided formally as follows:

- A set, $\mathcal{D}$, of stationary devices that may include sensors, IoT and other stationary devices. Each of the devices is defined in terms of an ordered pair that identifies its location in the two-dimensional Cartesian plane and its rate requirements. The information may be for individual devices, or groups of devices. Each group can be treated collectively as one point of service. If the requested service rates change, then this information may be updated with time.
- A set, $\mathcal{M}(\sqcup)$, of mobile devices, e.g., user equipments (UEs), service vehicles, etc. Each device is defined in terms of an ordered pair which identifies its location in the two-dimensional Cartesian plane and its rate requirements at time t. Due to mobility, the locations of devices have to be updated with time.
- The total bandwidth available for communications which consists of a set, $\mathcal{W}$, of fixed bandwidth channels. A device in the sets of stationary or mobile devices $\mathcal{D}$ or $\mathcal{M}$ may use one or multiple of these channels, depending on the rate requirements, the channel gains between the device and the associated UAV, as well as interference from other UAVs.

The rates identified for a device can be regarded as minimum required rates. The type of service and the requested service duration are also important in planning a service and the devices to be committed. For example, service due to a disaster is very different from service due to an increased traffic demand. In the first case there is no service and guaranteeing a minimal level of service is important. In the second case, service is available, but the network is congested, and service improvement is requested.

The decision phase requires that the demand be provided using a certain characterization and a certain model, and this applies to the characterization of $\mathcal{D}$, $\mathcal{M}(\sqcup)$, and $\mathcal{W}$. Several models have been developed for characterizing the spatial distribution of wireless traffic, and this has been done using 2-D and 3-D point processes. The surveys in [12], [13] provide an account of these models. Also, mobility discovery and prediction have been dealt with in the literature using stochastic processes and machine learning, as surveyed in [14]–[16].

We identify three classes of demand, and for each class the collection and characterization of the demand is different:

(a) **Fully characterized demand:** This is mostly a demand that is based on information available from service providers based on their service records. This demand characterization is used in the formulation of a static dimensioning problem, as described in the next phase. The use case also dictates how soon this information can be found. In serving disaster areas with predictable disasters, such as a hurricane, service providers may provide this information just before the disaster hits. In unpredictable disasters, such as earthquakes, a snapshot of the last available workload profile could serve as the workload characterization.

(b) **Partially characterized demand:** Some information, such as users distributions and their demands may be partially available, and these can be used as a starting point to construct statistical models of the demands which can be used in dimensioning. UAVs, in addition to acting as service points, may also collect local information in order to refine the demand characterization. Machine learning plays an important role in profiling the demand, and in characterizing and predicting mobility patterns.

(c) **Uncharacterized demand:** In some cases the information may not be available. An initial assumption about the demand characterization can be made, but similar to the second case the UAVs will also collect local information that better characterize the demand. Machine learning also contributes to the demand profiling and the prediction of mobility patterns, e.g., [17], [18].

Different mechanisms can be used for demand discovery and collection. As an example, the minimization drive test (MDT) that was introduced by 3GPP in Release 10 [19] makes use of UEs' measurements and reports to operators information, including locations, signal quality, etc. UAVs can fly and act as scouts to discover UEs and collect the MDT vectors from them. The UAVs will act as base stations at different locations, hence the MDT vector can be treated as both demands at those locations and UAV service quality. The UAVs flying trajectories, while acting as scouts, are optimally computed to expeditiously and comprehensively cover the possible service areas in order to collect information about UEs and their demands. The probable service areas may be discovered in phases based on their priority and likelihood of existing demands.

In addition to collecting fully characterized demand, machine learning techniques can be used to learn and classify different demand types and their locations. Demand types may be classified according to levels of bandwidth requirement, latency and loss rates. Deep learning algorithms can also be used to capture and predict users mobility and their demands. To improve accuracy and expedite convergence, deep learning can be combined with probabilistic latent semantic analysis in order to characterize different classes of users traffic and their mobility [17].

IV. DECISION AND DIMENSIONING PHASE

In this phase, the information collected in the demand phase is used to determine the number of UAVs, their locations, and the bandwidth assignments to provide the requested service. For the sake of illustration, we focus on downlink communications only. Backhauling is implemented in a distributed manner between UAVs using multi-hop communications to the nearest stationary base station (Fig. 2).

(a) **Short-term dimensioning:** To provide a service to the set of stationary devices defined above, a subset of the UAVs will act as base stations. The objective of the dimensioning problem is twofold: (1) Minimize the number of UAVs, and (2) maximize their operational lifetime. These two objectives may be contradictory since one may be able to reduce the number of UAVs but they will have to cover wider geographical areas, hence consuming more energy and depleting their batteries faster. Therefore, the dimensioning phase is solved as a dual objective optimization problem:

$$\text{Minimize} \quad (\mathrm{f_U}, -\mathrm{f_T}), \tag{1}$$

where f_U is the number of used UAVs and f_T is a function of their lifetimes. f_T can be expressed as the minimum lifetime among all UAVs and minimizing $-f_T$ corresponds to maximizing the minimum lifetime among all UAVs. The lifetime of a UAV depends on its battery energy available for communications after subtracting the mechanical energy. The UAV's lifetime is obtained by dividing this energy by the power used for communications. The mechanical energy used by the UAV to fly to a hovering location, and from the hovering location to a charging station, is dependent on the chosen location for the UAV. The optimal hovering location of a UAV at a certain time is in the three-dimensional Cartesian plane. As explained above, if the demand is defined according to a stochastic process, the above optimization problem will be formulated as a stochastic optimization problem.

There are two types of communications in which the UAVs are involved, and these influence the use and sharing of the bandwidth: UAV-to-user and UAV-to-UAV communications. These are captured in the dimensioning phase by using two association matrices:

(1) The device-UAV association, which is captured using a matrix with appropriate dimensions, where each matrix element is a binary variable that equals one if the device indicated by the row uses the UAV indicated by the column. Typically, each device is constrained to use exactly

one UAV. Determining whether a UAV is used can be obtained from this matrix, which is also used to obtain the number of needed UAVs.

(2) If UAVs communicate between themselves using the same RF spectrum, then a symmetric UAV-to-UAV association matrix with appropriate dimensions is defined. A matrix element is one if two UAVs communicate.

The dimensioning phase evaluates the above two matrices, and the power used for communication between UAVs and UEs, as well as between UAVs. It also determines the downlink rates to devices and guarantees that the spectrum is shared between the above two types of communications and achieves the minimum required rate, even with interference. The interference depends on the channel gain between pairs of devices, and the distances between them. The backbone rate is also a function of the rate of communications between the UAVs and their served UEs and is determined by the backbone routing. Interference is not present if OFDMA is used. A third objective may be added to cater for the case in which the resources are not sufficient, and this will be the maximum violation of the bit rate among all devices. This objective will be minimized.

Solving the optimization problem expressed by the objective function (1), and constraints formulated based on the above discussion, should result in the optimal dimensioning including the number and hovering locations of UAVs and their association with users, as well as their transmission power levels. The solution will be a Pareto front of the non-dominated solutions. Solving this problem is not easy due to a number of reasons: (i) It is a dual objective optimization problem; (ii) the device-UAV and UAV-UAV association problem is a combinatorial optimization problem that is NP-hard; and (iii) it is highly non-convex. Therefore, approximations and heuristics may be employed to solve this optimization problem within a reasonable time. Solution approaches include device clustering, binary variable relaxation, successive convex approximation and evolutionary programming approaches.

(b) **Long-term dimensioning:** This is similar to short-term dimensioning, except that the characteristics of the UAVs used for long-term service are taken into consideration. Since energy efficient UAVs can stay afloat for a long time, they will need to adapt to changing traffic demands and they may also use high power levels for communication, hence achieving higher rates and covering wider areas. Transitioning from short-term to long-term needs to consider the coexistence of UAVs of different types and capabilities. The simplest approach is to deploy all long-term UAVs and then withdraw all short-term UAVs, but this may also be done incrementally.

V. DEPLOYMENT AND TRAJECTORY PLANNING PHASE

The information from the demand and decision phases play a significant role in the deployment and trajectory planning phase. Information from the decision phase, such as the rate requirements for users, can affect the trajectories. For example, obtaining good channel gains between UAVs and users requires, in general, the UAVs to move closer to users expecting an increase in the achievable rate. On the other hand, the information from the decision phase, such as the number of UAVs and bandwidth limitation, will directly affect the deployment and trajectory design by limiting the available resources to use.

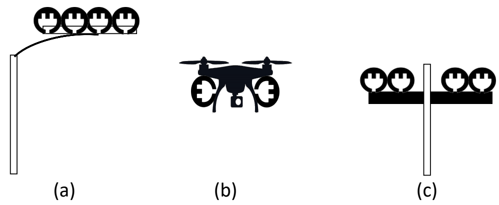

Fig. 3. Different types of charging stations: (a) Stationary, (b) mobile, and (c) semi-stationary.

We categorize the ground users into stationary and mobile. The only difference between these two types is that the speed of stationary users is set to zero. By exploiting a careful trajectory design of the UAVs, significant performance gains can be achieved compared to traditional wireless systems. However, several energy and safety factors need to be considered.

(a) **Instantaneous battery levels:** Each UAV determines its battery level periodically to make sure it has enough battery for both hovering and communication.

(b) **Charging stations types:** We consider three types of charging stations as shown in Fig. 3: (1) Stationary: Charging stations at pre-determined locations that cannot be moved, (2) semi-stationary: UAVs that take some time to deploy, e.g., balloons, which can be connected to a power grid or large batteries, but they can be deployed in optimal and strategic locations to recharge other UAVs, and (3) mobile: UAVs with large batteries that fly around and recharge other UAVs. Note that for stationary and semi-stationary types, each charging station can accommodate a maximum number of UAVs at a time. Therefore, each UAV needs not only find the optimal trajectory, but also the best charging station type. In the case of stationary users, the selections of trajectories and charging station type of the serving UAVs can be optimized offline (i.e., non-instantaneous optimization). On the other hand, in the case of dynamic users (variable users' locations with time), the selections of trajectories and charging station type of the UAVs are optimized online (i.e., instantaneous optimization). This is due to the variations of the qualities of communication channels over time. The online optimization will enhance the performance; however, it will add more complexity to the problem by optimizing the decision variables based on users' movements.

(c) **Recharging period:** This is the time the UAV needs to stay in the charging station, which depends on the decision of the central control unit based on the user's demand.

(d) **Safe path planning:** The UAVs are required to avoid flying over some restricted regions, such as airports. Also, they are required to avoid obstacles, such as buildings, or collisions with other UAVs.

Assuming that we have a certain number of charging locations, with a maximum UAVs that can be accommodated in each charging station, two constraints need to be respected. First, the maximum number of UAVs that can be charged during each time slot at each charging station. Second, to avoid collisions, no more than one UAV can be at the same location during the same time slot. Therefore, the possible scenarios are as follows: (1) The UAV moves between the serving location and the charging station, (2) the UAV stays at the same serving location, (3) the UAV moves from one serving location to another serving location, and (4) the UAV decides to remain in the charging station.

VI. SERVICE PHASE

In the service phase, the proper coverage service to achieve end-to-end connectivity will be provided. This includes communications between UAVs and ground users (stationary or mobile), between UAVs, and between access points and the core network. In order to provide UaaS for end-to-end connectivity, it is critical to establish a reliable backbone network between UAVs to allow reliable and low-latency data delivery either from a UAV to a base station, or from a base station to one or more UAVs, or from a base station to another base station through a network of UAVs.

Many of the existing works on routing in UAV networks have typically used classic mobile ad-hoc networks (MANET) protocols. These protocols can be classified as either proactive [20]–[22] or reactive [23], [24], depending on whether they maintain routes *a priori* or build routes on demand. Hybrid protocols, such as hybrid wireless mesh protocol (HWMP) of the IEEE 802.11s standard, also exist [25]. However, these classic protocols usually perform poorly in UAV networks where nodes are generally moving fast.

Some other works have adapted MANET protocols for their use in UAV networks [26]. For example, ML-OLSR [27] is a mobility- and load-aware version of OLSR, and P-OLSR (Predictive OLSR) [28] uses GPS information to predict link states based on relative speed and direction of the UAVs. Other modifications of OLSR specifically for UAV networks include COLSR [29] and DOLSR [30]. A cluster-based, location-aided version of DSR for UAV networks is proposed in [31]. Other UAV network routing protocols include GPMOR [32], a geographic routing protocol that considers mobility and orientation, and RGR [33], a protocol that combines reactive and geographic routing. Although these efforts have been successful in handling some of the scenarios of UAV networks, more innovations are needed to improve the reliability and latency performances of the routing protocols.

We introduce three possible approaches to deal with routing in the dynamic and challenging environment of UAV networks.

(a) **Proactive routing based on cohesive swarming and machine learning:** Unlike conventional MANETs, designing optimal multi-path routing and congestion control algorithms for UAV networks is particularly challenging due to the highly dynamic and energy-aware UAV flight maneuvers, which yields constantly changing network topology and fluctuating channel qualities. Classic MANET routing methods are known to perform poorly in such environments. One possible way of enhancement is to combine them with cohesive swarming which coordinates UAVs to form a swarm that suits best the underlying routing method, as well as the locations of the base stations or charging stations and the events or users of interest. In addition, machine learning techniques can be used for more accurate traffic prediction and thus enhancing in-routing functions among UAVs [34], [35]. This type of methods may work well in situations where the locations of base stations, charging station, and events or users of interest are known *a priori* and thus it is possible to plan the routing and swarming strategies in advance [36].

(b) **Fast-converging reactive routing:** In addition to accurate predictive proactive routing, designing fast-converging reactive routing methods also plays a critical role in UAV networks. In classic reactive methods, queue-length changes are often used as weights in making dynamic routing decisions. Such methods are known to converge slowly. One possible way to improve the convergence speed is to couple queue-length changes with route update from the previous time slot (called momentum). Momentum-based reactive routing methods such as the one proposed in [37] could be a good candidate for routing in UAV networks, due to its low-complexity, and its strong performance guarantees in terms of throughput-optimality, delay reduction, and convergence speed. This type of methods may work better in situations where the locations of events or users of interest may not be completely known *a priori* before the UAVs are deployed.

(c) **Anycast-based opportunistic routing:** Opportunistic routing refers to the practice of making routing decisions dynamically (instead of following predetermined routes) based on network events and conditions, such as link availability and quality. The opportunistic approach gives nodes multiple options for forwarding a packet and, thus, may particularly be suited for UAV networks where a node's neighbors can be constantly changing. The cross-layer approach proposed in [38] could be a candidate for opportunistic routing in UAV networks. This approach merges information from both network and link layers to make dynamic routing decisions based on the available links. Moreover, the opportunistic approach may be integrated with the first two methods to further improve the system performance.

VII. CASE STUDIES

A. *Case Study 1: UaaS for Self-Healing*

A.1 Description

We present here a case study that illustrates the application of the D^3S framework. This case study addresses the failure of ground base stations (GBSs) and the application of the D^3S framework to provide a backup coverage for the failed GBSs. GBS failures can be classified as short-term and long-term. Short-term failure is defined as the failure that lasts for a short period of time (few hours). The long-term failure can last for a few days.

In our case study and based on different types of UAVs documented in [11], rotary-wing drones are proposed to mitigate the short-term failures as they have an important feature of instant deployment. Moreover, the operational power consumption of these drone BSs (DBSs), i.e., UAVs, is very high, resulting in a limited flying/service time, which is suitable for short-term deployment. On the other hand, Helikites are proposed to mitigate long-term failures as they fly at low altitudes and for long periods of time, being tethered to a continuous source of power. Based on Fig. 2, where a disaster scenario is considered, other

UAVs/DBSs will be used in the healing process, if the failure is short-term or until Helikites are deployed.

In the presented scenario, if the failure is short-term, UAVs will be used in the healing process. However, if it is a long-term failure, Helikites will be used. For the short-term failure scenario, we apply the D^3S framework as follows:

Demand: Once the network operator detects a failure, a request is placed with a set of parameters related to the failed GBS, i.e., location, area, number of users, and bandwidth.

Decision: Based on the previous request, and since it is a short-term failure, the decision will be taken based on the collected data from the demand phase, i.e., the number of users and requested bandwidth. The number of UAVs needed to heal the failed GBS and their deployment locations will be decided based on an optimization problem.

The formulated optimization problem will aim to maximize the minimum achievable rate of the UEs under the failed GBS and meanwhile minimizing the transmission power of the UAV used which also minimizes the total number of UAVs used.

$$\underset{\mathbf{J},\Phi,\Psi,\mathbf{p}}{\text{maximize}} \frac{\Omega}{R^{\text{th}}} - \frac{1}{P^{\max} * |\mathcal{D}|} \sum_{d} \sum_{u} \sum_{m} \psi_{u,d} \Phi^{m}_{u,d} p^{m}_{u,d}. \quad (2)$$

The optimization variables are the UAV coordinates $\mathbf{J}$, the DBS-UE association Ψ, the resource allocation binary variable Φ, and the transmission power of the UAV $\mathbf{p}$. Note that Ω is an auxiliary continuous variable used to represent the maximization of the minimum achievable rate of the UEs [39].

The optimization problem is subject to the following constraints: (i) Resource allocation and user association constraints, (ii) minimum achievable rate constraint, and (iii) 2D coordinates constraint to limit the coverage/service area of each UAV given that they all fly at the same altitude.

Deployment: The deployment depends mainly on the initial DBS locations and the trajectory is determined optimally. In Fig. 2, the initial location of a particular DBS is shown to be above a certain building.

Service: A minimum achievable rate is guaranteed to the users in the affected area. The location of the serving DBSs can change based on the mobility of users.

For long-term failures, the application of the D^3S framework is exactly the same as the short-term failure, except for the type of UAVs. Based on the demand, we may use Helikite(s) only (if the application is not time sensitive) or DBSs first until deploying the Helikites since their deployment can take up to 45 minutes. In this case, the DBSs will heal the users until the Helikites are deployed and then the DBSs will return back to their initial locations.

A.2 Numerical Results

Numerical results are provided to investigate the benefits of using different types of UAVs to mitigate GBS failure using the D^3S framework. The optimization problem presented in this section is solved using General Algebraic Modeling System (www.gams.com). The simulation area is 400×400 m^2 and the UEs are distributed randomly. In this case study, we consider that the users are static and the UAVs move dynamically based on the optimization problem.

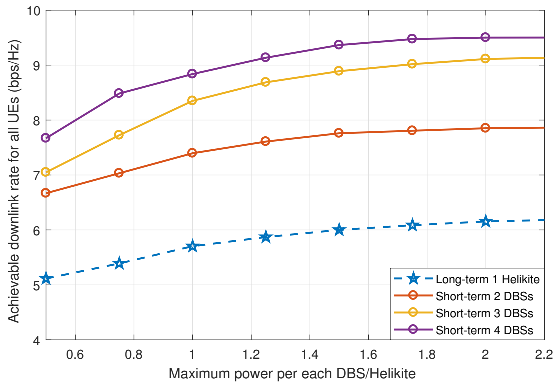

Fig. 4. Achievable downlink rate for all UEs © 2018 IEEE.

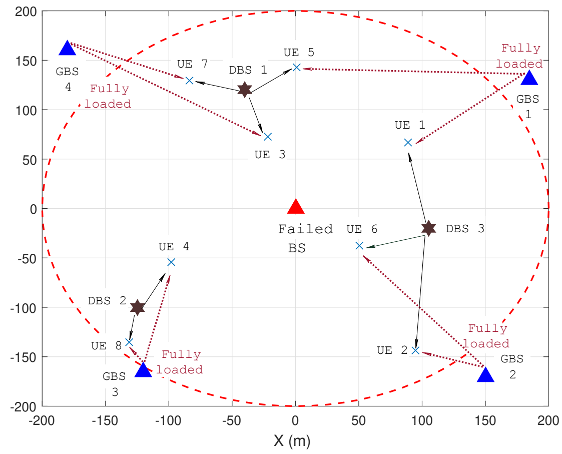

Fig. 5. DBSs serving all UEs of the failed BS © 2018 IEEE.

Fig. 4 represents a mitigation performance for short-term and long-term failures in terms of the achievable downlink rate for static UEs. By increasing the number of used DBSs/UAVs, the consumed power increases. As the maximum power increases, the rate increases but levels off when the power reaches 1W [40]. Owing to the fact that the objective function of the optimization problem is maximizing the minimum achievable rate and at the same time minimizing the downlink power, there is a trade-off between increasing the achievable rate and decreasing the downlink power. The long-term scenario, which uses one Helikite, results in the lowest achievable rate. This is because the Helikite altitude is higher than that of the DBSs.

Fig. 5 shows a short-term failure scenario where the failed GBS (shown as a red triangle) is centered in the middle and other fully loaded GBSs are distributed near the edge. Based on the decision phase, three DBSs are ready to serve the users. Dotted red lines show the scenario if any of the GBSs is not fully loaded. In this case, the UEs will be associated with this particular GBS and the DBS will return back to its initial location. It worth noting that DBS1 and DBS2 utilize less than 50% of their maximum power since in this scenario not all UEs are associated with one DBS. On the contrary, DBS4 utilized around 95%

of its maximum power. This is because more than three UEs are connected to DBS4.

B. Case Study 2: UaaS for Dynamic Users

B.1 Description

In the second case study, we apply the D^{3}S framework to the case of dynamic users. This case study considers a wireless relaying system consisting of mobile users aiming to transmit their data to a given sink. We assume that mobile users and the sink are out of communication ranges and they are communicating through multiple UAVs. The D^{3}S framework can be applied as follows:

Demand: Because of mobile users and sink are out of communication range, the network operator places a request to connect the mobile users with the sink.

Decision: Because UAVs are battery operated, based on the demand request, the decision will be taken to optimize the needed number of UAVs, energy consumption, power allocation, and association between UAVs and users. For fairness, the formulated optimization problem will aim to maximize the sum of the achievable data rates while respecting: (i) Transmit power budget, (ii) UAVs' battery level, and (iii) trajectory limitations. We assume that each UAV can employ a decode-and-forward strategy. The objective function can be expressed as follows:

$$\underset{\mathbf{J},\boldsymbol{\Psi},\mathbf{P_d}}{\text{maximize}} \sum_{d} \sum_{u} \sum_{m} \min \left[R^{m}_{u,d}(J, \Psi, P_d), R^{m}_{d,0}(J, P_d) \right], \quad (3)$$

where $R^{m}_{u,d}(J, \Psi, P_d)$ and $R^{m}_{d,0}(J, P_d)$ are the achievable data rate from mobile user u to UAV d over bandwidth m and from UAV d to sink, respectively.

Deployment: Because of the dynamic nature of the mobile users, the UAV trajectory has to be updated regularly. Given a predefined trajectory of UAVs, we can update/adjust the trajectory under some boundary constraints to enhance the provided throughput to users. Hence, we optimize the user-UAV association, in addition to the UAVs' transmit power levels, while taking into consideration the communication channel quality.

Service: A minimum achievable rate is considered for mobile users.

B.2 Numerical Results

Fig. 6 plots the UAV trajectories using updated and pre-planned trajectory for one UAV. Note that the updated trajectory can be adjusted based on users' location. In Fig. 7 [41], we plot the achieved average throughput per user versus users' transmit power for updated and pre-planned trajectory approaches. It shows the improvement of updated trajectory approach over the pre-planned trajectory approach (for static users) in terms of average throughput. This is because the updated trajectory approach has a higher degree of freedom by modifying the trajectory of the UAV to be close to users as much as possible to enhance the channel gain and the total throughput.

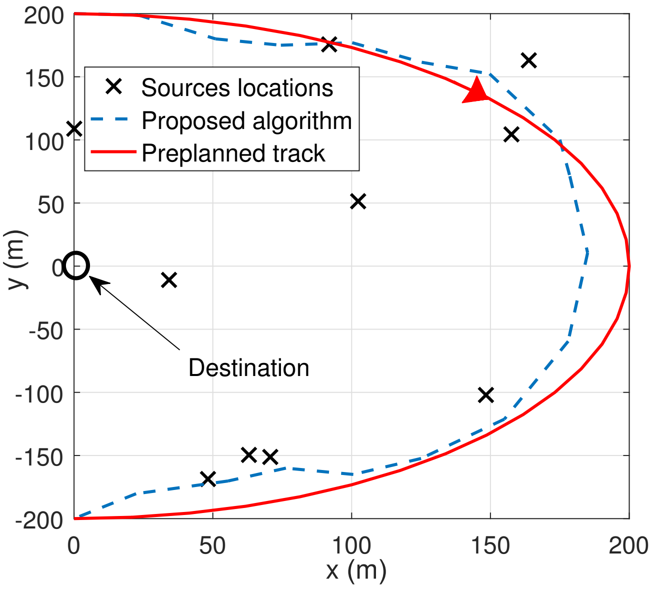

Fig. 6. The updated and preplanned trajectories © 2018 IEEE.

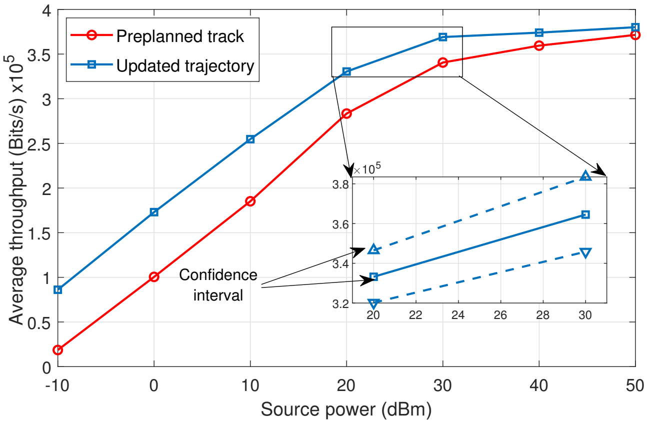

Fig. 7. Average throughput vs. users' transmit power © 2018 IEEE.

VIII. CONCLUSION

We have introduced a novel framework of UaaS and showcase its usage in the context of wireless connectivity service. Based on four phases of *Demand*, *Decision*, *Deployment*, and *Service*, the main objectives of this framework is to develop efficient and realistic solutions to implement these four phases. To evaluate the performance of this framework, we illustrated its application in two case studies. The first case study addresses the failure of one or more GBSs of a wireless cellular network and shows how we can mitigate the effect of this failure to keep the wireless connectivity service operational using the D^{3}S framework. The second case study considers a wireless relaying system between one GBS and dynamic users. Depending on the time requested by the users, the drones are able to modify their trajectories to provide effective connectivity services.

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