Taming Aerial Communication with Flight-assisted Smart Surfaces in 6G Era

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Abstract—Aerial communication is gradually taking an assertive role within common societal behaviors by means of unmanned aerial vehicles (UAVs), high-altitude platforms (HAPs), and fixed-wing aircrafts (FWAs). Such devices can assist general operations in a diverse set of heterogeneous applications, such as video-surveillance, remote delivery and connectivity provisioning in crowded events and emergency scenarios. Given their increasingly higher technology penetration rate, telco operators started looking at the sky as a new potential direction to enable a three-dimensional (3D) communication paradigm.

However, designing flying mobile stations involves addressing a daunting number of challenges, such as an excessive onboard control overhead, variable battery drain and advanced antenna design. To this end, the newly-born Smart Surfaces technology may come to help: reconfigurable intelligent surfaces (RIS) may be flexibly installed on-board to control the terrestrial propagation environment from an elevated viewpoint by involving low-complex and battery-limited solutions. In this paper, we shed light on novel RIS-based use-cases, corresponding requirements, and potential solutions that might be adopted in future aerial communication infrastructures.

I. INTRODUCTION

Aerial communications, whereby flying devices such as unmanned aerial vehicles (UAVs), fixed-wing aircrafts (FWAs) or high-altitude platforms (HAPs) are used to facilitate the communication between two given nodes in the network, are a well-established technology capable of providing powerful yet highly flexible platforms to enhance and complement current fifth generation (5G) and beyond network infrastructures (6G) [1]. Such kind of deployments, denoted as air-to-ground (A2G) networks, are envisioned as an integral part of future internet of things (IoT) networks thanks to their agility to act as portable on-demand base stations (BSs), flexibility to move in space, and an overall increased probability of high-end-to-channel quality. As a matter of fact, unlike fixed BSs, flying devices can be exploited on-demand and reused for different applications, e.g., assisting rescue operations after natural disasters via user localization and (re)establishing a damaged or unavailable network infrastructure [2]. In addition, they are able to hover avoiding obstacles that may cause blockage. Thus, significantly increasing the probability of establishing a line-of-sight (LoS) with terrestrial users, giving rise to the new three-dimensional (3D) communication paradigm in the 6G era.

However, despite its potentials and envisioned business opportunities, aerial communications are hindered by the limited power budget and maximum carrying load of flying devices. E.g., in the case of UAVs it poses significant constraints on its feasibility: carrying bulky, heavy, and power-hungry equipment such as active antennas on board results in high design complexity and capital expenditure; further limiting the application range of aerial communications. Moreover, conventional A2G networks require signal processing capabilities on-board, e.g., for channel estimation or precoding, and frequent backhaul communications, which further compound the design complexity of such systems.

To overcome the above-mentioned issues, there has been growing interest in the emerging reconfigurable intelligent surface (RIS) technology, which is widely recognized as the means to greatly improve the quality of wireless communication links towards 6G networks (A2G communications) as depicted in Fig. 1 [1][4]. RISs are two-dimensional surfaces divided into unit cells spaced at a sub-wavelength distance, which can reflect the incoming signal by adding a given tunable phase shift. As a result, the reflected signal components can be combined constructively at the intended receiver position and destructively elsewhere in a nearly-passive way [5]. Moreover, RISs can be fabricated to be extremely lightweight (hundreds of grams) and consume as little as tens of milliwatts, as opposed to conventional BSs that weight few Kilograms and consume tens of Watts. Thereby, making them suitable for being rapidly deployed in B5G/6G networks at affordable costs.

While the opportunities of RIS-aided A2G networks are well-understood, several design aspects still need to be addressed in order to unlock its full potential. Indeed, the joint
optimization of the RIS and BS configuration, as well as the aerial device trajectory, require an adaptive level of control and signaling able to cope with the degree of mobility of the specific application scenario, including: unpredictable movements typical of aerial objects, corresponding maneuvering and a limited power budget available on board. All such aspects pose strict limitations on the A2G control architecture, making its design extremely challenging.

In this paper, we identify the main optimization aspects to be considered when designing a RIS-aided A2G network by describing its main characteristics and corresponding state of the art (SoA) solutions. We further shed light on technical challenges and open research directions and characterize two relevant operating scenarios. We finally deliver the message that while joint exploitation of RIS energy-efficient beamforming capabilities and flexible and agile aerial communications requires a careful design of the control architecture, it might significantly boost the overall communication performance.

II. RIS-AIDED A2G NETWORKS

RISs can be integrated in the context of aerial communications in two different ways, namely i) terrestrial RIS, i.e., by mounting them on the facade of buildings in order to assist in the communication to/from the flying object and ii) aerial RIS, i.e., by employing them as substitutes to bulky active components such as conventional BSs on board the flying device [7]. However, while deploying terrestrial RISs can help alleviate the total power consumption, it does not fundamentally solve the problem of limited operation range of e.g. UAVs. On the other side, by allowing the UAV to carry an inherently light-weight and passive device on board such as an RIS, nearly all the available power can be devoted to enlarge the range of operation while simultaneously achieving highly selective beamforming. The RIS itself might even be (partially) powered by harvesting power from the incoming signals, which further demonstrates the feasibility of aerial RISs [7]. Moreover, terrestrial RISs can only achieve 180° reflection angles, compared to the full-angle 360° of aerial RISs, which allows to effectively cover the intended two-dimensional target area. Therefore, we focus on aerial RISs as depicted in Fig. 1 and describe the main characteristics, involved opportunities, and corresponding challenges.

The link budget of an A2G network is directly proportional to the signal wavelength and the number of RIS elements, and inversely proportional to the distance to the user [3]. On the one hand, the increasing demand for higher communication rates and the need to support a massive number of users is pushing future wireless networks towards higher frequency bands, such as millimeter-wave (mmWave) or terahertz (THz). Hence, the signal wavelength is typically small and will likely tend to diminish, which further compounds the problem of correctly designing A2G networks. On the other hand, while the received power at the ground user can be linearly increased by making RIS elements dense, UAVs can carry only a limited payload thus resulting in a maximum feasible RIS dimension. Note that to overcome this problem, RIS-equipped UAV swarms can be deployed, i.e., a group of aerial RISs that cooperate together [9]. However, such cooperation comes at a significantly increased cost in terms of control overhead and complexity. It is thus of paramount importance to optimize the location of the aerial platform in order to obtain the best possible propagation conditions to the ground users in terms of increased LoS probability and limited pathloss.

Beamforming at the RIS can increase the received power at the intended location up to a maximum theoretical factor equal to the square of the number of elements. In order to take full advantage of such tremendous capabilities, advanced 3D passive beamforming algorithms and techniques at the RIS are needed, especially in the multi-user scenario, which requires addressing complex non-convex problems.

Moreover, current 5G BSs are usually equipped with a multi-antenna array, which endows them of active beamforming capabilities. The optimization of both active and passive beamforming vectors is intrinsically coupled with the optimization of the position of the flying device and its evolution over time (i.e., its trajectory). Such joint optimization is in general intractable and requires to resort to suboptimal approaches or heuristics. In particular, an efficient approach is decoupling the two problems in an alternating fashion. The trajectory optimization is efficiently solved via machine learning (ML) tools such as deep networks, while the passive beamforming optimization problem can be tackled via successive convex approximation (SCA) or semidefinite relaxation (SDR) [10].

In the multi-user scenario, one can alternatively schedule users with a time division multiple access (TDMA) scheme [11] or, in order to improve fairness and robustness, consider max-min approaches thereby assigning at each user a given figure of merit such as, e.g., the signal-to-noise ratio (SNR) or the bit error rate (BER), and aiming at maximizing the worst figure among the target users [12].

The core of the joint trajectory and beamforming optimization in A2G networks is linked to the acquisition and tracking of channel state information (CSI). Indeed, an accurate system optimization requires the estimation of both the channel from the BS to the flying device and the channel from the latter to the target user. However, RISs are passive structures with no estimation nor processing capabilities, which poses several constraints on the applicability of classical pilot-based channel estimation techniques [13]. In addition, in real-life scenarios the users have a certain degree of mobility, which presents the highly challenging problem of tracking the evolution of the channel vectors over time. In this regard, it is essential to have accurate channel modeling that depends on few key system parameters. Thanks to the high LoS probability associated with the altitude of the aerial platform thereby enabling the 3D communication paradigm [4], the channel vectors are completely characterized by the distance travelled by the signal and the angle of arrival (AoA)/angle of departure (AoD) at the various entities in the network [14]. It is thus possible to realize efficient CSI acquisition in A2G networks by tracking the location of both the users and the flying device, which is feasible with a sufficient degree of control signalling.

III. A2G CONTROL ARCHITECTURE

As depicted on the left-hand side of Fig. 2 SoA control architectures for A2G networks in the case of UAVs are
typically divided into two separate layers: ground control station and aerial platform control. The former is physically located in the terrestrial network and it consists of a processing unit that, given a set of policies and quality of service (QoS) requirements, jointly optimizes the UAV trajectory and both the active and passive beamforming at the BS and at the RIS, respectively. Moreover as described above, it deals with acquiring CSI and extracting the associated relevant channel parameters. Whereas, the aerial platform control is given by the on-board UAV controller and the RIS controller. While the former is dedicated to the maneuvering of the UAV, the latter triggers RIS settings (i.e., predefined phase shifts).

A widely adopted assumption in SoA control architectures is to consider the UAV in a predefined location in space with negligible orientation and position variations during the communication phase, while its position is updated only within the displacement phase. However, such assumption does not hold in practical scenarios, wherein the UAV maneuvering and several atmospheric phenomena can change the position and the orientation of the UAV even during the communication operations, leading SoA solutions to be potentially inefficient—or even unfeasible—to operate in realistic conditions. Indeed, as the UAV is hovering at a certain altitude, its motion is influenced by a deterministic component, which is due to the intentional maneuvering of the UAV, i.e., following a predefined trajectory, and a random component, due to unpredictable factors such as atmospheric conditions including wind, rain, and humidity, imprecise maneuvering, non-ideal UAV instrumentation, etc. Such movements result in translations and rotations of the surface of the on-board RIS, which in turn lead to misalignment of the transmit and reflected beams. This effect is further exacerbated by the highly directive nature of mmWave beamforming at the RIS and can ultimately result in loss of connectivity at the user-side [15].

To get the most from A2G networks in a practical scenario, the mitigation of UAV mobility effects on the QoS is a key point. It is thus essential to design enhanced control architectures enabling a transmission optimization tightly coupled with the UAV mobility pattern. Indeed, UAVs are equipped with different sensors, such as gyroscope, compass, global positioning system (GPS), etc., that provide the UAV controller with motion feedback enabling hovering control and stabilization. However, due to the separation of the UAV and RIS controllers, information on UAV movements is only partially considered during the system optimization phase, i.e., only the nominal position of the UAV is considered to perform CSI acquisition and joint trajectory and beamforming optimization, while information such as real-time maneuvering instructions and UAV sensors’ output is typically neglected. Fig. 2 shows the framework that we envision to enable interaction between the UAV and the control architecture. In particular, on the right-hand side we consider two distinct artificial intelligence (AI)-based modules dubbed as on-board intelligence and in-network intelligence, which are located on the UAV, and at the network-side, respectively. The on-board module interacts both with the UAV and the RIS controllers. It plays the fundamental role of collecting mobility information from the UAV and integrating it into the communication optimization process. Interestingly, the in-network intelligence module communicates both with the on-board module and with the standard communication optimization module. Our proposed novel framework is thus capable of blending together the various conventionally separated system entities and effectively utilizing all the available precious information to suitably optimize both RIS and BS parameters such as, e.g., beamforming configurations and transmit power at the BS.

IV. KEY-DESIGN ASPECTS

To describe our envisioned enhanced control architecture, we first identify the key aspects that significantly affect its design. As depicted in Fig. 3, an A2G network can explore three main directions: i) the total available power budget,
thus giving rise to low computational power, whereas less critical applications such as data streaming may accept a larger latency but require a higher rate, which is typically associated with an increased computational power. In this regard, we identify three categorizations namely unconstrained, feasible, and limited power availability.

Reconfiguration rate. The choice of reconfiguration rates enables different QoS guarantees and overall achievable communication rate. We determine three degrees of increasing reconfiguration rate dubbed as intermittent, regular, and frequent. For low reconfiguration rates, the system can devote most of the available time for sending/receiving data to/from the users. However, the available information from the UAV sensors, user feedback, and the CSI acquisition is only sporadically updated. As a result, the performance might be acceptable only for low mobility scenarios or when the atmospheric conditions are ideal. Whereas for frequent reconfiguration rate the available information is continuously updated and as a result, the communication quality can be generally maximized even under high user mobility and strong meteorological perturbations. However, this implies an increased overhead that negatively affects the overall data rate. An intermediate solution is given by regular reconfiguration rates, which is the case of robust optimization algorithms, i.e., schemes that employ statistical channel and perturbation information rather than costly instantaneous CSI.

Maneuvering. The UAV maneuvering is either handled by the network itself, i.e., it is coupled with the optimization of the system, or by an operator like in disaster situations, in which the information about the UAV position is feedback based from the control device. In such scenarios, the network can access useful information from the UAV sensors and can accurately track the CSI as the UAV moves. In the second case, the UAV maneuvering might be under the control of an external entity and is thus disjoint from the rest of the system optimization. Hence, the CSI and the UAV position must be regularly estimated in order to keep an acceptable level of performance.

V. RIS-AIDED A2G CASE STUDIES FOR 6G

Hereafter, we describe a practical implementation of our proposed enhanced control architecture considering two relevant case studies when RIS technology is in place.

Case study: Static UAV. The relevant scenario of interest is depicted in Fig. 4. Assume that due to low mobility of ground users a UAV is in a fixed location in space, which is only seldomly updated. However, due to adverse atmospheric conditions, the UAV is subject to unwanted perturbations, which result in undesired roll, yaw, and pitch of the surface of the on-board RIS. UAV movement counteractions are automatically taken but still orientation oscillations or location perturbation may result in an instantaneously RIS misconfiguration, leading to misalignment of the reflected beams and degraded overall achievable rate. Remarkably, it has been recently shown that it is possible to guarantee an acceptable level of performance in the target area of influence by suitably adjusting the beamforming configuration as a function of the second-order statistics of such perturbations. Such adaptation of the
system configuration is enabled by our proposed enhanced control architecture. Indeed, the measurements of the instantaneous roll, yaw and pitch are collected by the UAV controller and sent to the UAV data processing module that extracts or predicts (e.g., using AI) the relevant statistics. This information is then used upon request to update the current CSI and optimize the communication to/from the UAV. In particular, the beamforming configuration can be optimized on the basis of the current perturbation statistics via: i) conventional mathematical tools such as SDR, ii) by training a ML model that learns how to adapt the beamforming configuration to the varying atmospheric conditions, or iii) by designing an online AI learning algorithm. The choice of optimization method determines the computational power expenditure, which has a direct impact on the total power availability. As a result, our proposed enhanced control architecture can be designed to have a feasible or unconstrained power availability.

As the UAV is in a fixed position, the RIS and BS precoders can be updated only when needed, i.e., when the perturbation statistics evolve due to a change of atmospheric conditions. Our proposed enhanced control architecture provides two ways to deal with such a scenario, which are characterized by an intermittent and regular reconfiguration rate, respectively. A first approach is to exploit feedback monitoring: users in the service area can periodically send updates to the network with the current perceived QoS. The in-network intelligence devoted to the CSI acquisition issues a statistics update request to the UAV data processing module if relevant changes in the QoS are detected.

A second approach is based on proactively sending updates on the UAV perturbation statistics when a relevant change is detected from the UAV data processing module to the CSI acquisition module. The latter then decides whether the relevant system parameters, such as the beamforming configurations, should be updated. This approach leads to higher power consumption at the UAV due to continuous monitoring and increased communication overhead. On the other hand, it allows to quickly react to the varying environmental conditions and minimize network downtime.

Lastly, note that both aforementioned approaches can be realized under coupled or feedback-based maneuvering. Indeed, in such cases, the UAV is controlled by the network and can thus retrieve useful information from the UAV controller. Whereas, a disjoint implementation would make it unfeasible to extract statistical information on the unwanted perturbations of the UAV position.

**Case study: Nomadic UAV.** We consider the practical case where a UAV is subject to desired movements in space, i.e., following a predetermined trajectory, as depicted in Fig. 5.

For simplicity, we neglect user mobility in order to focus on providing coverage enhancement within a given target service area. The drone movements lead to a continuous position and orientation change of the on-board RIS. Such effect, if not properly addressed, could lead to severe beam misalignment, and potentially to complete service disruption. Therefore, to maintain a stable connection, a continuous adaptation of both the RIS configuration and the BS precoder is required.

Referring to the degrees of freedom highlighted in Section IV, we consider the UAV maneuvering to be either coupled, i.e., the UAV trajectory is imposed by decisions taken at the network-side and therefore jointly optimized with the beamforming strategy, or feedback-based, i.e., the UAV is controlled by an external operator (e.g., a member of first responder teams) and therefore, its movements are not perfectly known to the network.

In the case of coupled maneuvering, the communication optimization module can compute in advance the RIS and the BS beamforming configuration according to the UAV trajectory evolution. Meanwhile, thanks to the UAV sensors data, the on-board data processing module can track the effective trajectory evolution, compare it against the desired one, and feed back information in case of divergence (e.g., non-idealities of the UAV controller, wind, etc.). Thus enabling suitable adjustment of both the beamforming and the maneuvering, and improving the overall reliability and robustness of the system. Depending on the power availability and variety of sensors equiping the UAV, the on-board data processing module can be further exploited. For example, visual information from cameras could be used to perform object detection and reveal potential obstruction (e.g., buildings, trees, or debris) and adapt the UAV trajectory accordingly.

Whereas in the case of feedback-based maneuvering, the
UAV movements are known at the network-side only a-posteriori. Therefore, to prevent the communication optimization from lagging behind the UAV movements, a trajectory prediction strategy could be applied to the on-board data processing module. Such prediction could take advantage of both the sensor data and the maneuvering feedback, while the trajectory forecast could be sent to the network-side to compute the optimal beamforming configuration in advance, so as to enable a more accurate transmission adaptation to the UAV movement.

The need for continuous communication adaptation, specific of the nomadic UAV scenario, results in a control architecture design that has to sustain a relatively high reconfiguration rate, i.e., regular or frequent. This implies a potentially high control overhead to frequently transmit the RIS configuration to the RIS controller. Nonetheless, smart overhead reduction strategies can be implemented thanks to the proposed enhanced control architecture. Indeed, the reconfiguration can be avoided as long as the QoS is within the desired level, despite the movement of the UAV. Therefore, a rate adaptation strategy could be considered to trigger the reconfiguration only when needed, e.g. based on the users’ feedback monitoring, thus minimizing the communication overhead. Moreover, the RIS configuration typically exhibits regular and periodic patterns over the surface elements. This peculiarity can be exploited by advanced encoding and decoding techniques, e.g., auto-encoders, that could be easily implemented in-network (encoding) and on-board (decoding) to further reduce the overhead. Such an additional feature would stress the computational load of the on-board intelligence module and in turn reflect on the power availability requirements. As a result, this scenario is characterized by limited or feasible power availability.

VI. DISCUSSION

The performance of our proposed enhanced control architecture in the application scenario described in Section V are hereafter summarized, for the case of feedback-based maneuvering, i.e., in the presence of an external UAV operator. We consider an A2G network including one single-antenna BS, one UAV equipped with a 100 element squared RIS and a target single-antenna user located at a distance of 70 meters from the BS. We assume the operator moves the UAV following a trajectory encircling the user with a radius of 25 m, altitude of 20 m, and with a given variable speed. The working frequency is set to 30 GHz, while the transmit power at the BS is fixed to 24 dBm and the noise spectral density is assumed to be $-80$ dBm.

In Fig. 6 we compare two different schemes, namely our proposed enhanced control architecture dubbed as Adaptive and the standard SoA control framework namely Fixed. We vary the UAV speed from 5 to 50 km/h and consider two different choices of reconfiguration rate, denoted as Frequent in solid lines and Regular in dashed lines. Thanks to our proposed control architecture, the in-network intelligent modules receive feedback from the UAV maneuvering, the UAV sensors and the user-perceived QoS and use it to adapt the system reconfiguration rate to the current UAV mobility rate and effective trajectory. In particular, as shown on the right-hand side, our proposed scheme adapts the CSI and RIS
beamforming strategy more frequently for an increasing UAV speed. On the one hand this generates higher overhead, which is shown as a percentage of the total available transmission time. On the other hand, the data rate is kept high and quasi-constant for the case of frequent reconfiguration rate thanks to the up-to-date CSI, which in turn leads to high SNR. In contrast to this, the standard architecture does not have access to the aforementioned UAV and QoS status information and thus, uses a pre-determined refresh rate to perform CSI acquisition and RIS beamforming optimization, as is typically the case for directional communications such as mmWave. In this case, the communication overhead is constant versus the UAV speed, while the data rate monotonically decreases. However, at low UAV speeds, the standard scheme obtains higher data rates at the cost of an increased overhead as compared to the proposed enhanced scheme.

VII. CONCLUSIONS

Aerial communications are opening a new research direction to enable a 3D mobile networking paradigm expected to be effective in the 6G landscape. However, a number of daunting challenges need to be addressed before the dream of cost-effective flying mobile stations solutions can be reached, in particular with respect to the design of the control architecture.

In this paper, we analyzed the novel concept of RIS-aided aerial communications and shed the light on some of its potential use cases, optimization aspects, and challenges. Specifically, we argued that a carefully designed enhanced control architecture is essential in order to take full advantage of the RIS 3D passive beamforming capabilities and the flexibility of flying devices. In contrast to existing SoA frameworks, our envisioned enhanced control architecture is able to bridge together several conventionally isolated entities and exploit useful information generated by the UAV sensors (in addition to the user feedback on the perceived QoS) in order to adapt the system configuration to varying environmental conditions.

We analyzed two practical scenarios of interest wherein the underlying A2G network benefits from our proposed architecture and quantified its performance in a relevant case study. Our results show that i) our proposed Adaptive scheme is able to adapt the CSI and RIS beamforming strategy as required according to varying UAV speeds, ii) the adaptability comes at a non-negligible reconfiguration overhead cost of about 5 to 15% and iii) the proposed adaptive solution successfully manages to keep the data rate at low degradation percentages (< 10%) for the UAV speed range considered (5 to 50 km/h).

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