Interference Avoidance Position Planning in Dual-Hop and Multi-Hop UAV Relay Networks

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Abstract—We consider unmanned aerial vehicle (UAV)-assisted wireless communication employing UAVs as relays to increase the throughput between a pair of transmitter and receiver. We focus on developing effective methods to position the UAV(s) in the presence of interference in the environment, the existence of which makes the problem non-trivial and our methodology different from the current art. We study the optimal position planning, which aims to maximize the (average) signal-to-interference-ratio (SIR) of the system, in the presence of: i) one major source of interference, ii) stochastic interference. For each scenario, we first consider utilizing a single UAV in the dual-hop relay mode and determine its optimal position. Afterward, multiple UAVs in the multi-hop relay mode are considered, for which we investigate two novel problems concerned with determining the optimal number of required UAVs and developing an optimal distributed position alignment method. Subsequently, we propose a cost-effective method that simultaneously minimizes the number of UAVs and determines their optimal positions to guarantee a certain (average) SIR of the system. Alternatively, for a given number of UAVs, we develop a fully distributed placement algorithm along with its performance guarantee. Numerical simulations are provided to evaluate the performance of our proposed methods.

Index Terms—UAV, relay networks, jamming, interference avoidance, position planning, interference mitigation.

I. INTRODUCTION

RecentlY, unmanned aerial vehicles (UAVs) have been considered as a promising solution for a variety of critical applications such as environmental surveillance, public safety, disaster relief, search and rescue, and purchase delivery [2]. In wireless networks, UAVs have been considered as aerial base stations for content delivery and caching [3], [4]. Considering relaying as one of the most elegant data transmission techniques in wireless communications [5]–[7], one of the recent applications of UAVs is utilizing them as relays in wireless networks [8]–[10]. Constructing a UAV communication network for such applications is a non-trivial task since there is no regulatory and pre-allocated spectrum band for the UAVs. As a result, this network usually coexists with other communication networks, e.g., cellular networks [11], [12]. Thus, studying the problem of interference avoidance/mitigation for the UAV communication network is critical, where the inherent mobility feature of the UAVs can be deployed as an interference evasion mechanism. This fact is the main motivation behind this work.

In most of the related literature, the position planning for a single UAV, which is considered either as a gateway between a set of sensors and a ground node or as a relay node between a pair of transmitter and receiver, is developed [13]–[23]. In [13], the optimal position of a set of UAV relays is studied to improve the network connectivity and communication performance of a team of ground nodes/vehicles, where there is no communications among the UAVs themselves. In [14], a UAV is employed as a mobile relay to ferry data between two disconnected ground nodes. This work aims to maximize the end-to-end throughput of the system by optimizing the source/relay power allocation and the UAV’s trajectory. In [15], UAV-assisted relay networks are studied in the context of cyber-physical systems, where a relay-based secret-key generation technique between two UAVs are proposed. In [16], optimal deployment of a UAV in a wireless relay communication system is studied in order to improve the quality of communications between two obstructed access points, while the symbol error rate is kept below a certain threshold. In [17], UAVs are utilized as moving relays among the ground stations with disconnected communication links in the event of disasters, where a variable-rate relaying approach is proposed to optimize the outage probability and information rate. In [18], UAV-enabled mobile relaying in the context of the wiretap channel is proposed to facilitate secure wireless communications, the goal of which is to maximize the secrecy rate of the system. In [19], considering the usage of a UAV as relay between a pair of transmitter and receiver, an end-to-end throughput maximization problem is formulated to optimize the relay trajectory and the source/relay power allocations in a finite time horizon. In [20], a UAV works as an amplify-and-forward relay between a base station and a mobile device.
The trajectory and the transmit power of the UAV and the transmit power of the mobile device are obtained aiming to minimize the outage probability of the system. In [21], the placement of a UAV in both static and mobile relaying schemes is investigated to maximize the reliability of the network, for which the total power loss, the overall outage, and the overall bit error rate are used as reliability measures. Also, it is shown that the decode-and-forward relaying is better than amplify-and-forward relaying in terms of reliability. In [22], position planning of a UAV relay is studied to provide connectivity or a capacity boost for the ground users in a dense urban area, where a nested segmented propagation model is proposed to model the propagation from the UAV to the ground user that might be blocked by obstacles. In [23], the optimization of propulsion and transmission energies of a UAV relay is considered, where the problem is studied as an optimal control problem for energy minimization based on dynamic models for both transmission and mobility. Studying the UAV placement planning in the multi-hop relay communication context, in which multiple UAVs can be utilized between the transmitter and the receiver, is a new topic studied in [24]–[27]. The aim of these works is similar to the aforementioned literature; however, data transmission through multiple UAVs makes their methodology different. Moreover, there are some similar works in the literature of sensor networks, among which the most relevant ones are [28], [29]. In [28], the two-dimensional (2-D) placement of relays is investigated aiming to increase the achievable transmission rate. In [29], the *impromptu* (as-you-go) placement of the relay nodes between a pair of source and sink node is addressed considering their distance as a random variable, where the space is restricted to be 1-D. Utilizing the mobility feature of the UAVs is one of the main differences between our work and relevant studies focused on ground relay placement. This feature allows reconfiguration of the UAVs’ positions with respect to (w.r.t.) the position of a (potentially moving) jammer, and also motivates us to propose online distributed position planning methods requiring iterative position re-adjustments of the UAVs. Finally, an orthogonal problem is to study the effective jammer positioning in UAV-assisted relay networks [30].

None of the aforementioned works consider the placement of UAV(s) in the presence of interference in the environment. This work can be broken down into two main parts. In the first part, we aim to go one step beyond the current literature and investigate the UAV-assisted wireless communication paradigm in the presence of a major source of interference (MSI), which refers to the source of interference with the dominant effect in the environment. Considering different interpretations for the MSI, e.g., a primary transmitter in UAV cognitive radio networks [11], [31], an eNodeB in UAV-assisted LTE-U/WiFi public safety networks [32], a malicious user in drone delivery application, or a base station in surveillance application, our paper can be adapted to multiple real-world scenarios. Given the intractability of direct analysis upon having multiple sources of interference in the network, we later show that the interference caused by multiple sources of interference with known locations can be modeled as the interference of a single hypothetical MSI, making our framework and analysis applicable to a wider range of applications. In the second part, we consider a distinct scenario, in which, due to the limited knowledge of the positions of the sources of interference or the time varying nature of the environment, we model the interference as a stochastic phenomenon. For each part, we study the optimal placement planning upon having a single UAV, i.e., dual-hop single link scheme, and multiple UAVs, i.e., multi-hop single link scheme, acting as relays between the transmitter and the receiver. The existence of interference renders our methodology different compared to the current literature; however, the previously derived results can be considered as especial cases in our model by assuming that the MSI is located too far away or it possesses an insignificant transmitting power. Hence, the methodology proposed in this work can motivate multiple follow up works revisiting the previously studied problems considering the presence of interference in their models. Moreover, compared with the relevant literature on multi-hop UAV-assisted relay communication, e.g., [24]–[27], mostly focused on obtaining the optimal location/trajectory of the UAVs, in addition to incorporating the interference into our model, we introduce and investigate two new problems: i) determining the minimum required number of UAVs and their locations so as to satisfy a desired (average) signal-to-interference-ratio (SIR), or equivalently data rate, of the system; ii) developing a distributed placement algorithm, which requires message passing only among adjacent UAVs to maximize the (average) SIR of the system.

A. Contributions

1) We investigate the problem of optimal UAV position planning considering the effect of interference in the environment in the decode-and-forward relay communication context for both the dual-hop and the multi-hop relay settings. We pursue the problem considering i) the existence of an MSI in the network, and ii) stochastic interference. Moreover, we propose and investigate two novel problems in the multi-hop relay setting: i) determining the minimum required number of UAVs and their optimal positions, and ii) developing a distributed position alignment algorithm.

2) Considering a single UAV and an MSI, we develop a theoretical approach to identify the optimal position of the UAV to maximize the SIR of the system in the dual-hop setting. We also address the position planning for a single UAV upon having stochastic interference.

3) In the multi-hop relay context, considering the existence of an MSI, we develop a theoretical framework that simultaneously determines the minimum required number of UAVs and their optimal positions so as to satisfy a predetermined/desired SIR of the system. We also develop a similar framework considering the stochastic interference in the environment and investigate the optimally of our approach upon having independent and identically distributed (i.i.d.) and non-i.i.d interference along the horizontal axis.

4) In the multi-hop relay context, considering the existence of an MSI and given the number of UAVs, we propose...
an optimal distributed algorithm that achieves the maximum attainable SIR of the system, which only requires message exchange among the adjacent UAVs. We also propose a distributed position planning considering stochastic interference and investigate its optimality upon having i.i.d. and non-i.i.d. interference along the horizontal axis.

II. PRELIMINARIES

We consider data transmission between a pair of transmitter (Tx) and receiver (Rx) co-existing with a major source of interference (MSI). We consider a left-handed coordination system \((x, y, h)\), where the Tx, the Rx, and the MSI are assumed to be on the ground plane defined as \(h = 0\). The locations of the Tx, the Rx, and the MSI are assumed to be \((0, 0, 0)\), \((D, 0, 0)\), and \((X_{\text{MSI}}, Y_{\text{MSI}}, 0)\), respectively. In practice, the location of the MSI can be estimated using jammer localization techniques (see [33] and references therein). We assume \(0 \leq X_{\text{MSI}} \leq D\) for simplicity, which can be readily generalized with minor modification. The transmission powers of the Tx, the UAV, and the MSI are denoted by \(p_t\), \(p_u\), and \(p_{\text{MSI}}\) respectively. To improve the transmission data rate, it is desired to place a UAV or a set of UAVs, each of which acting as a relay, between the Tx and the Rx. To have tractable solutions, we assume that the UAVs are placed at \(y = 0\) plane. While such a constraint imposes certain limitations to our study, it allows us to obtain some first analytical results that provide insightful guidance for practical design in general and also are meaningful for some specific application scenarios. Also, considering legal regulations, we confine the altitude of the UAVs to \(h \in [h_{\text{min}}, h_{\text{max}}]\).

We consider the line-of-sight (LoS) and the non-line-of-sight (NLoS) channel models, for which the path-loss is given by:

\[
L_{\text{LoS}}^{i,j} = \mu_{\text{LoS}} d_{i,j}^{\alpha} \quad L_{\text{NLoS}}^{i,j} = \mu_{\text{NLoS}} d_{i,j}^{\alpha},
\]

where \(\mu_{\text{LoS}} \triangleq C_{\text{LoS}} (4\pi f_c/c)^\alpha\), \(\mu_{\text{NLoS}} \triangleq C_{\text{NLoS}} (4\pi f_c/c)^\alpha\), \(C_{\text{LoS}}\) is the excessive path loss factor incurred by shadowing, scattering, etc., in the LoS (NLoS) link, \(f_c\) is the carrier frequency, \(c\) is the speed of light, \(\alpha = 2\) is the path-loss exponent, and \(d_{i,j}\) is the Euclidean distance between node \(i\) and node \(j\). The link between two UAVs (air-to-air) is modeled using the LoS model, while the link between the MSI and the Rx (ground-to-ground) is modeled based on the NLoS model. To model the link between a UAV and the Rx/Tx/MSI (air-to-ground and ground-to-air) either the LoS or the NLoS model [25], [26] or a weighted average between the LoS model and the NLoS model [34]–[36] can be used. In this paper, we consider a general case and denote the path-loss between a UAV \(i\) and node \(j\) located on the ground by \(\eta_{\text{NLoS}} d_{i,j}^2\). We assume that \(\eta_{\text{NLoS}}\) is constant in the range \(h \in [h_{\text{min}}, h_{\text{max}}]\), and thus \(\eta_{\text{NLoS}} \triangleq g(\mu_{\text{LoS}}, \mu_{\text{NLoS}}, h_{\text{min}}, h_{\text{max}})\), where \(g\) is a function. Further discussions on obtaining the \(g\) are given in [33]–[36].

III. POSITION PLANNING FOR A SINGLE UAV CONSIDERING AN MSI

Let \(\text{SIR}_1\), \(\text{SIR}_2\) denote the SIR at the UAV located at \((x, 0, h)\) and the SIR at the Rx, respectively (see Fig. 1), which are given by:

\[
\text{SIR}_1(x, h) = \frac{p_t / (\eta_{\text{NLoS}} d_{\text{UAV,Tx}}^2)}{p_{\text{MSI}} / (\eta_{\text{NLoS}} d_{\text{MSI}}^2)} = \frac{p_t (x-X_{\text{MSI}})^2 + y^2 + h^2}{p_{\text{MSI}} (x^2 + h^2)},
\]

\[
\text{SIR}_2(x, h) = \frac{p_u / (\eta_{\text{NLoS}} d_{\text{UAV,Rx}}^2)}{p_{\text{MSI}} / (\eta_{\text{NLoS}} d_{\text{MSI}}^2)} = \frac{p_u (y^2 + (D-X_{\text{MSI}})^2)}{p_{\text{MSI}} (D-x)^2 + h^2}. \tag{2}
\]

Considering the conventional decode-and-forward relay mode, the SIR of the system \(\text{SIR}_S\) is given by [25]:

\[
\text{SIR}_S(x, h) = \min \left\{ \text{SIR}_1(x, h), \text{SIR}_2(x, h) \right\}, \forall x, h. \tag{3}
\]

Assuming equal bandwidths for both links, maximizing the data rate between the Tx and the Rx is equivalent to maximizing the \(\text{SIR}_S\) by tuning the location of the UAV described as:

\[
(x^*, h^*) = \arg \max_{x \in [0, D], h \in [h_{\text{min}}, h_{\text{max}}]} \text{SIR}_S(x, h). \tag{4}
\]

The presence of an MSI renders our approach different from most of the works mentioned in Section I mainly due to its
effect on the SIR expressions making them non-convex w.r.t. the position of the UAV(s), which leads to the inapplicability of the conventional optimization techniques. In this work, we exploit geometry and functional analysis to obtain the subsequent derivations. In the following, we propose two lemmas, which are later used to derive the main results in Theorems 1-3. In these lemmas, first we obtain the locus of the points satisfying the same value of the SIR that will be used to obtain the optimal position of the UAV when both the altitude and the horizontal position of the UA V are variable. Second, we investigate the behavior of the SIR expressions, which will facilitate our discussion and derivation. In the interest of space, the proofs are provided in the extended version of this paper [37].

**Definition 1:** In geometry, a locus is the set of all points satisfying the same conditions or possessing the same properties.

**Lemma 1:** The locus of the points satisfying $\text{SIR}_1(x, h) = \text{SIR}_2(x, h)$ is given by the following expression:

$$h^\pm = \sqrt{\Lambda^\pm(x)},$$

with $\Lambda^\pm(x) = [−B(x) \pm \sqrt{B^2(x) − 4A(x)C(x)}]/(2A(x))$, where $A(x)$, $B(x)$, and $C(x)$ are given by (6), shown at the bottom of the page.

**Proof:** Please refer to [37].

**Lemma 2:** For $\text{SIR}_1$, the stationary point [38] w.r.t. $x$, $\Psi^x$, is given by:

$$\Psi^x = \frac{Y^2_{\text{MSI}} + X^2_{\text{MSI}} + \sqrt{(Y^2_{\text{MSI}} + X^2_{\text{MSI}})^2 + 4X^2_{\text{MSI}}h^2}}{2X_{\text{MSI}}},$$

(7)

Also, $\text{SIR}_1$ has no stationary point w.r.t. $h$ when $h \in (h_{\text{min}}, h_{\text{max}})$. With $\Psi^h \triangleq \frac{Y^2_{\text{MSI}} + X^2_{\text{MSI}}}{2X_{\text{MSI}}}$, we have

$$\begin{align*}
\frac{\partial \text{SIR}_1(x, h)}{\partial x} & \geq 0 \text{ if } x \geq \Psi^x, \\
\frac{\partial \text{SIR}_1(x, h)}{\partial x} & < 0 \text{ O.W.}, \\
\frac{\partial \text{SIR}_1(x, h)}{\partial h} & \geq 0 \text{ if } x \geq \Psi^h, \\
\frac{\partial \text{SIR}_1(x, h)}{\partial h} & < 0 \text{ O.W.}.
\end{align*}$$

(8)

Moreover,

$$\max_{x \in [0, D], h \in [h_{\text{min}}, h_{\text{max}}]} \text{SIR}_1(x, h) = \frac{p_t(X^2_{\text{MSI}} + Y^2_{\text{MSI}} + h^2)_{\text{min}}}{p_{\text{MSI}}h^2_{\text{min}}}.$$

(9)

In this work, $+$ and $-$ superscripts denote the larger and the smaller solution, respectively.

On the other hand, $\text{SIR}_2$ has no stationary point when $x \in (0, D), h \in (h_{\text{min}}, h_{\text{max}})$ and

$$\begin{align*}
\frac{\partial \text{SIR}_2(x, h)}{\partial h} & \leq 0, \\
\frac{\partial \text{SIR}_2(x, h)}{\partial x} & \geq 0, \\
\forall x \in [0, D], h \in [h_{\text{min}}, h_{\text{max}}],
\end{align*}$$

(10)

and

$$\max_{x \in [0, D], h \in [h_{\text{min}}, h_{\text{max}}]} \text{SIR}_2(x, h) = \frac{p_t\mu_{\text{NLoS}}(Y^2_{\text{MSI}} + (D - X_{\text{MSI}})^2)}{p_{\text{MSI}}h_{\text{min}}^2}.$$
least a feasible solution. Let \( x_{\text{sol}} \) denote the smallest solution, if \( \text{SIR}_1(x_{\text{sol}}, \hat{h}) \geq \text{SIR}_1(D, \hat{h}) \) then \( x^* = x_{\text{sol}} \); otherwise, \( x^* = D \).

**Case 5** \( \text{SIR}_1(0, \hat{h}) \geq \text{SIR}_2(0, \hat{h}) \) and \( \psi^x < D \) and \( \text{SIR}_1(\psi^h, \hat{h}) \geq \text{SIR}_2(\psi^h, \hat{h}) \); the quartic equation may or may not have a feasible solution and \( x^* = D \).

**Proof:** Please refer to [37].

**Remark 1:** The constraints expressed in multiple cases of the above theorem can be interpreted from a different perspective, which leads to a practical guide to designing \( p_i \) and \( p_u \) w.r.t. the position of the MSI. Alternatively, they can disclose useful information to the malicious user to effectively place the MSI. This interpretation also holds for Theorem 2 and 3 below.

For more information please refer to [37] (in particular see Corollary 1 and the subsequent discussion in that reference).

2) Finding the Optimal Vertical Position \( h^* \) of the UAV for a Given Horizontal Position \( x = \hat{x} \): In this case, the vertical positions (altitudes) satisfying (5) can be easily derived since \( \Lambda^\pm(x) \) on the right hand side of the equation is known. Using Lemma 2, we obtain the following theorem to identify the optimal position of the UAV.

**Theorem 2:** Given a fixed horizontal position \( x = \hat{x} \), the optimal altitude \( h^* \) of the UAV is given by:

- **Case 1** \( \hat{x} \leq \Psi^\hat{h} \): 
  \( h^* = h_{\text{min}} \).

- **Case 2** \( \hat{x} > \Psi^\hat{h} \) and (5) has a feasible solution (either \( h^+ \) or \( h^- \) belong to \( [h_{\text{min}}, h_{\text{max}}] \) ); \( h^* \) is the same as the feasible solution of (5).

- **Case 3** \( \hat{x} > \Psi^\hat{h} \) and (5) has no feasible solution: \( h^* \) can be derived by solely inspecting the boundary positions:
  \[
  h^* = \arg\max_{h \in [h_{\text{min}}, h_{\text{max}}]} \text{SIR}_S(\hat{x}, h).
  \]  

**Proof:** Please refer to [37].

3) Finding the Optimal Position When Both \( h \) and \( x \) of the UAV are Adjustable: In the previous scenarios, the locus defined in (5) reduces to an equation since one variable (either \( h \) or \( x \)) is given, which is not the case here. In this case, the optimal position of the UAV is identified in the following theorem.

**Theorem 3:** Let \( \Lambda \) denote the set of all the feasible solutions of the locus described in (5). The optimal position of the UAV \( (x^*, h^*) \) is given by:

- **Case 1** If the Locus has no solution, the optimal position can be derived by solely examining the boundary positions:
  \[
  (x^*, h^*) = \arg\max_{(x, h) \in \{(0, h_{\text{min}}), (0, h_{\text{max}}), (D, h_{\text{min}}), (D, h_{\text{max}})\}} \text{SIR}_S(x, h).
  \]  

- **Case 2** Upon having at least one feasible solution for the locus, if \( \text{SIR}_2(D, h_{\text{min}}) \leq \max\{\text{SIR}_1(D, h_{\text{max}}), \text{SIR}_1(D, h_{\text{min}})\} \), \( (x^*, h^*) = (D, h_{\text{min}}) \). Also, if \( \text{SIR}_1(0, h_{\text{min}}) \leq \text{SIR}_2(0, h_{\text{min}}) \), \( (x^*, h^*) = (0, h_{\text{min}}) \).

Otherwise, let \( (\hat{x}, \hat{h}) = \arg\max_{(x, h) \in \Lambda} \text{SIR}_S(x, h) \), then the optimal position of the UAV is given as follows:

- If \( \psi^x < D \) and \( \psi^h \leq \hat{x} < \psi^x \) and \( \text{SIR}_1(\hat{x}, \hat{h}) \geq \text{SIR}_1(D, h_{\text{max}}) \), \( x^* = D \) and \( h^* \) can be derived using Theorem 2 considering \( \hat{x} = D \).

- If \( \psi^x < D \) and \( \hat{x} < \psi^x \) \( x^* = \hat{x} \) and \( h^* \) can be derived using Theorem 2 considering \( \hat{x} = D \).

- If \( \psi^x < D \) and \( \psi^h \leq \hat{x} < \psi^x \) and \( \text{SIR}_1(\hat{x}, \hat{h}) \geq \text{SIR}_1(D, h_{\text{max}}) \), \( x^* = D \) and \( h^* \) can be derived using Theorem 2 considering \( \hat{x} = D \).

**Proof:** Please refer to [37].

### IV. Position Planning for Multiple UAVs Considering an MSI

We investigate the placement planning upon utilizing multiple UAVs from two different points of view. First, we consider a cost effective design, in which the network designer aims to identify the minimum required number of utilized UAVs and determine their positions so as to satisfy a predetermined SIR of the system. Second, we assume that the network designer is provided with a set of UAVs, and endeavors to configure their positions so as to maximize the SIR of the system. We assume that the UAVs utilize the same frequency but different time slots to avoid mutual interference among the UAVs.

#### A. Network Design to Achieve a Desired SIR

Let \( \gamma \) denote the desired SIR of the system and assume that \( N \) is the minimum number of UAVs needed to satisfy the SIR constraint, which will be derived later. We index the Tx node by 0, the UAVs between the Tx and the Rx from 1 to \( N \), and the Rx node by \( N+1 \). We denote the horizontal distance between two consecutive nodes \( i \) and \( i+1 \), \( 1 \leq i \leq N+1 \), and consider \( d = [d_1, \ldots, d_{N+1}] \). To have tractable derivations, we assume that all the UAVs have the same altitude \( h \) (see Section IV-C for more details). The model is depicted in Fig. 2. Let \( \text{SIR}_k \) denote the SIR at the \( k \text{th} \) node, which can be obtained as:

\[
\begin{align*}
\text{SIR}_1(d, h) &= \frac{p_{u}\eta_{\text{ds},1}^{-1}(\sqrt{d_1^2 + h^2})^{-2}}{P_{\text{ds}}\eta_{\text{ds},1}^{-1}(\sqrt{(X_{\text{msi}} - d_1)^2 + Y_{\text{msi}}^2 + h^2})^{-2}}, \\
\text{SIR}_2(d, h) &= \frac{p_{u}\eta_{\text{ds},1}^{-1}(\sqrt{d_2^2})^{-2}}{P_{\text{ds}}\eta_{\text{ds},1}^{-1}(\sqrt{(X_{\text{msi}} - d_2 - d_1)^2 + Y_{\text{msi}}^2 + h^2})^{-2}}, \\
& \vdots \\
\text{SIR}_{N}(d, h) &= \frac{p_{u}\eta_{\text{ds},1}^{-1}(\sqrt{d_N})^{-2}}{P_{\text{ds}}\eta_{\text{ds},1}^{-1}(\sqrt{(X_{\text{msi}} - d_N) - d_1)^2 + Y_{\text{msi}}^2 + h^2})^{-2}}, \\
\text{SIR}_{N+1}(d, h) &= \frac{p_{u}\eta_{\text{ds},1}^{-1}(\sqrt{d_{N+1}^2 + h^2})^{-2}}{P_{\text{ds}}\eta_{\text{ds},1}^{-1}(\sqrt{(X_{\text{msi}} - D)^2 + Y_{\text{msi}}^2})^{-2}}.
\end{align*}
\]  

(15)

Similar to the single UAV scenario, \( \text{SIR}_S \) is given by:

\[
\text{SIR}_S(d, h) = \min \{ \text{SIR}_1(d, h), \ldots, \text{SIR}_{N+1}(d, h) \},
\]

\forall d, h.

(16)
For this UA V, the stationary point $\Phi_i$ (with an MSI (multi-hop single link)).

1) The SIR Expressions and the Feasibility Constraints: From (15), it can be observed that achieving any desired SIR $\gamma$ may not be feasible. To derive the feasibility conditions for the $\gamma$, we need to analyze the links between the Tx and UAV, among the adjacent UAVs, and from UAV to the Rx.

Analysis of the links between the Tx and UAV (SIR$_1$) and between UAV and the Rx (SIR$_{N+1}$) is similar to the discussion provided in Section III (see Lemma 2). Hence, we skip them and consider the SIR at UAV, $2 \leq i \leq N$. For this UAV, the stationary point $\Phi_i$ of the SIR expression is given by:

$$\Phi_i = \frac{h^2 + Y^2_{\text{MSI}}}{X_{\text{MSI}}} - \sum_{j=1}^{i-1} d_j,$$

(17)

using which it can be validated that:

$$\max_{x \in [0,D], h \in [h_{\text{min}}, h_{\text{max}}]} \text{SIR}_i(x,h) \leq p_u \mu_{\text{tot}}^{-1} \left( \frac{\max(X_{\text{MSI}}^2, (D - X_{\text{MSI}})^2) + Y^2_{\text{MSI}} + h^2}{p_{\text{MSI}} h_{\text{MSI}}^{-1} d_{\text{min}}^2} \right),$$

(18)

and:

$$\frac{\partial \text{SIR}_i(x,h)}{\partial d_i} \geq 0 \quad \text{if } d_i \geq \Phi_i,$$

$$\frac{\partial \text{SIR}_i(x,h)}{\partial d_i} < 0 \quad \text{O.W.},$$

(19)

where $d_{\text{min}}$ is the minimum feasible distance between two UAVs considering the mechanical constraints. It can be verified that with tuning the locations of the middle UAVs any value for SIR$_i$ is achievable among the UAVs, when $\text{SIR}_i \leq p_u \mu_{\text{tot}}^{-1} \left( \frac{(Y^2_{\text{MSI}} + h^2)}{p_{\text{MSI}} h_{\text{MSI}}^{-1} d_{\text{min}}^2} \right)$. Combining these derivations with those in Section III, we obtain the feasibility condition declared in (20), shown at the bottom of the page.

2) Design Methodology: To derive the minimum number of needed UAVs and their optimal positions so as to satisfy a desired SIR$_S$, we aim to maximize the distance between the UAVs while satisfying the desired SIR of the system. Our approach can be described by the following three main steps:

(i) Considering SIR$_1$, for UAV$_1$, we obtain the maximum distance from the Tx (toward the Rx) $d_1^*$ that satisfies the SIR constraint and place the first UAV at the obtained location.

(ii) Considering SIR$_{N+1}$, for UAV$_N$, we obtain the maximum distance from the Rx (toward the Tx) $d_{\text{max}}^{\text{max}}$ that satisfies the desired SIR. (iii) Consider the segment with length $D - d_1^* - d_{\text{max}}^{\text{max}}$; we use the SIR expressions of the remaining UAVs to maximize the distance between the adjacent UAVs to cover the distance while satisfying the desired SIR$_S$. In the following, we explain these steps in more detail.

Considering SIR$_1$, we solve SIR$_1 = \gamma$, the answer of which is given by (21), shown at the bottom of the page. Then, using Lemma 2, $d_1^*$ is given by:

$$d_1^* = \begin{cases} d_1^* & \text{if } d_1^* > D, \\ d_1^* & \text{if } d_1^* < \Psi^* \text{ and } d_1^* \leq D, \\ D & \text{O.W.}. \end{cases}$$

(22)

In the last case of (22), the optimal number of UAVs is 1, and the UAV should be placed at $x = D$. Assuming $d_1^* < D$, using Lemma 2, the maximum distance between the last UAV and the Rx to satisfy the SIR constraint $d_{\text{max}}^{\text{max}}$ can be obtained as:

$$d_{\text{max}}^{\text{max}} = \sqrt{\frac{p_u \gamma \mu_{\text{tot}}^{-1} (X_{\text{MSI}} - D)^2 + Y^2_{\text{MSI}}}{\gamma p_{\text{MSI}} h_{\text{MSI}}^{-1}} - h^2},$$

(23)

Note that using Lemma 2 it can be verified that if the distance between UAV$_N$ and Rx is less than $d_{\text{max}}^{\text{max}}$, the SIR constraint at the Rx is always met. Afterward, we solve SIR$_k = \gamma$ and use (17)-(18) to obtain $d_k^*$, $2 \leq k \leq N$, given by:

$$d_k^* = \begin{cases} d_k^* & \text{if } d_k^* > D - \sum_{j=1}^{k-1} d_j, \\ d_k^* & \text{if } d_k^* < \Phi_k^* \text{ and } d_k^* \leq D - \sum_{j=1}^{k-1} d_j, \\ D - d_{\text{max}}^{\text{max}} & \text{O.W.}. \end{cases}$$

(24)

where $d_k^*$, $d_k^+$ are given in (25), shown at the bottom of the next page. Finally, the minimum number of required UAVs $N$ is given by:

$$N = \arg \min_{n \in \mathbb{N}} \sum_{k=2}^{n} d_k^* \geq D - d_1^* - d_{\text{max}}^{\text{max}}.$$  

(27)

According to (24) and (25), calculation of each $d_k^*$ only requires the knowledge of $d_{k'}^*$, $\forall k' < k$. Hence, the solution of (27) can be easily obtained by initially assuming $n = 2$ and increasing the value of $n$ by 1 until the constraint in the right hand side of the equation is met. Given the distances $d_1^*, \ldots, d_N^*$ from (27), we have $d_{N+1}^* = D - \sum_{k=1}^{N} d_k^*$, for which $d_{N+1}^* \leq d_{\text{max}}^{\text{max}}.$
B. Distributed Position Planning for a Given Number of UAVs

In this case, there exist multiple UAVs dedicated as relays to the network, which are expected to be positioned to maximize the SIR of the system. To this end, an algorithm can be immediately proposed based on our results in the previous subsection, which considers the number of UAVs as given and slowly increases the SIR ($\gamma$) starting from $\gamma = 0$ to find the maximum value of $\gamma$ for which $N$ in (27) becomes equal to the number of given UAVs. Afterward, the positions of the UAVs can be obtained as discussed before. Nevertheless, this is a centralized approach. In the following, we propose a distributed algorithm for the same purpose, where the UAVs locally compute their positions based on the knowledge of the positions of their adjacent neighbors, which can be obtained through simple message passing. The following fact is an immediate consequence of examining (25): with a known $d_1$ and a (hypothetically) given value for the SIR$_S$ ($\gamma$) starting with UAV$_1$, the distance between the subsequent UAVs can be obtained up to UAV$_N$ in a forward propagation, by which each UAV transmits its position to the adjacent UAV located toward the Rx (see (24), (25)). Note that in the mentioned propagation, no message is exchanged between the last UAV and the Rx, and thus the SIR at the Rx might be less than $\gamma$. For this purpose the last UAV uses (23) to derive the maximum distance from the Rx for which the SIR constraint is met; and thus the last UAV can immediately verify the satisfaction of the SIR constraint given its current location. We propose a distributed algorithm for position planning of multiple UAVs, the pseudo code of which is given in Algorithm 1. In this algorithm, we first locate the first UAV above the Tx and the last UAV above the Rx and derive the initial desired SIR$_S$ ($\gamma^{(0)}$); subsequently, we set the position of the first UAV to have $\gamma^{(0)}$ as the SIR of the first link (lines 1-3). Afterward, using forward propagation, the UAVs locally obtain their positions w.r.t. the position of their adjacent UAV (lines 4) so as to satisfy the desired SIR$_S$. Then, the satisfaction of the SIR at the Rx is inspected via UAV$_N$ using the current distance from UAV$_N$ to the Rx (line 5). If this SIR satisfies the desired SIR of the system at the current iteration, the algorithm stops; otherwise, it starts over with a new desired value for SIR$_S$, and readjusts the locations of UAVs in the next iteration (lines 6-11).

---

4We admit that in reality precise small adjustments of the locations of the UAVs may not be feasible due to physical hovering system limitations. However, this assumption is just needed to prove the optimality of the algorithm in theory. In reality, the error in the movements of the UAVs will result in a sub-optimal solution, which is unavoidable.

---

1) Computational Complexity and Convergence Analysis: At each iteration of our proposed distributed algorithm, in forward propagation mode, each UAV obtains its next location using a simple message passing with its adjacent UAV, through which the location of the adjacent UAV is exchanged, and calculation of a closed form expression (using (24)) is performed. Hence, at each iteration, the computational complexity of the tasks performed at each UAV is $O(1)$. Also, it is obvious that, given a step size $\epsilon \leq \gamma^{(0)}$, the algorithm performs at most $\lceil \gamma^{(0)}/\epsilon \rceil$ iterations. Thus, the worst computational complexity of our algorithm is $O(\gamma^{(0)}/\epsilon)$ at each UAV.

**Proposition 1:** For any given number of UAVs and a sufficiently small size of the step size $\epsilon$, assuming the same altitudes for the UAVs, Algorithm 1 always converges to the maximum achievable value of SIR$_S$.

**Algorithm 1:** Distributed Position Planning for Multiple UAVs in the Presence of a Major Source of Interference

**Input:** Step size $\epsilon$.

1. $i = 0$, $d_i^{(i)} = 0$, $d_{i+1}^{(i)} = 0$.
2. $\gamma^{(i)} = \min \{ SIR_1(d_1^{(i)}, h), SIR_{N+1}(d_{N+1}^{(i)}, h) \}$.
3. Derive $d_i^{(i)}$ for the target SIR $\gamma^{(i)}$ using (22).
4. Given $d_i^{(i)}$, obtain $d_2^{(i)}, \ldots, d_N^{(i)}$ using forward propagation based on (24) using $\gamma^{(i)}$.
5. Obtain the maximum distance $d_{\text{max}}$ from the Rx to satisfy the SIR constraint $\gamma^{(i)}$ using (23) at UAV$_N$.
6. if $D = \sum_{k=1}^{N} d_k^{(i)} > d_{\text{max}}$ then
7. Derive the next target SIR: $\gamma^{(i+1)} = \gamma^{(i)} - \epsilon$.
8. $i = i + 1$ and go to line 3.
9. else
10. Fix the UAVs at their current positions.

**Proof:** Please refer to [37].

C. Further Adjustment of the Altitudes and the Horizontal Distances of UAVs

The assumption made on the altitudes of the UAVs in the previous two subsections, i.e., the same altitude for all the UAVs, is common in current literature [25], [26], [42]–[44]. Nevertheless, it can be predicted that adjustment of the altitude of each UAV can further increase the SIR of the system. Note that due to the non-convexity of the SIR expressions, proposing an analytical solution that jointly optimizes the altitudes and the horizontal positions of the UAVs in the multi-hop setting is hard to achieve. With this consideration, we propose a heuristic algorithm in Algorithm 2, which takes
the horizontal distances of the UAVs obtained in the previous two subsections as the input and further adjusts the horizontal positions and altitudes of the UAVs.

The basic idea behind our algorithm is to increase the minimum SIR of all the adjacent pairs of links, which connect the Tx to the Rx, at each iteration. Considering (16), this results in increasing the SIR of the system at each iteration. At each iteration of Algorithm 2, each UAV aims to increase the minimum SIR of the two local links, i.e., the link connecting the previous node of the network to the UAV and the link connecting the UAV to the next node, that pass through it (lines 3,4). To this end, at each iteration, starting from the first UAV, each UAV explores the horizontal distances between itself and the two adjacent nodes and the range of altitudes specified by a vertical exploration parameter $e_h$ while the location of all the other UAVs are fixed (line 6). In other words, each UAV, $u_i$, with height $h_i$ explores a triangle area in the space, the width of which is the distance between its two adjacent nodes and the height of which is $2e_h$ ($h$ is in the range $[h_i - e_h, h_i + e_h]$). Then, it changes its location to the best found position corresponding to the maximum increase in the minimum SIR of its local links (line 9). Afterward, the next UAV aims to achieve the same goal considering the modified position of the previous UAV and the process continues until the last UAV adjusts its location, which completes one iteration.

The following three facts are immediate: i) the algorithm is convergent. ii) the SIR of the system achieved at each iteration of the algorithm is non-decreasing w.r.t. the iteration number. In other words, the algorithm always increases the SIR of the system by a value that is greater than or equal to zero from one iteration to the next. iii) Given the fact that through the position adjustment process, each UAV requires the locations of the two adjacent nodes and only conducts internal calculations, the algorithm can be implemented in a distributed fashion.

V. EXTENSION TO MULTIPLE SOURCES OF INTERFERENCE

Pursuing a similar approach to the previous two sections, i.e., obtaining the positions of the UAVs w.r.t. the position of the MSI, upon existence of multiple sources of interference (SI) is highly challenging. Nevertheless, in the following, we demonstrate that the results derived in the previous sections for a single MSI can be easily extended to this scenario to provide approximate solutions. Let $I = \{S_1, S_2, \ldots, S_L\}$ denote the set of SIs. Let $(x_i, y_i, 0)$ denote the position of $S_i$, $\forall i$. Assuming that the interference is superimposed, at any given point in the sky, $h > 0$, the total interference power at point $(x, y, h)$ is given by:

$$\kappa(x, y, h) = \sum_{i=1}^{L} \frac{p_i}{\eta_{\text{MSI}}} \left( \frac{x - x_i}{x^2 + y^2 + h^2} \right)^2.$$  

We model the effect of all the SIs as a single hypothetical MSI. For this purpose, we assume that the hypothetical MSI is placed at $(x_H, y_H, 0)$ with power $p_H$. The hypothetical MSI should exhibit a similar interference effect as the SIs in the sky. Hence, we formulate the problem of obtaining $x_H, y_H, p_H$ as minimizing the approximation error described in (26), shown at the bottom of the previous page, or the discretized version of it, i.e., replacing the integrals in (26) with summations, both of which can be solved numerically.

Another approach is to approximate (28) and the interference power expression of the hypothetical MSI using their Taylor expansions and obtain $x_H, y_H, p_H$ accordingly. Note that the approximation error depends on the positions and transmitting powers of the SIs. In general, the approximation error is lower when the SIs are closer to each other and have more homogeneous transmitting powers. Nevertheless, when
the mentioned criterion is not satisfied, the positions of the UAVs can be obtained by measuring the interference power in the environment, which is further discussed in the next section.

VI. Stochastic Interference

In some scenarios, the position of the MSI or the SIs are not known. Also, the number of interference sources, their positions, and their transmission powers may change over time, and thus not be fixed. In these scenarios, the interference can be considered as a random variable at each point in the sky. The distribution of this random variable at any point can be obtained by measuring the interference power at that point for a long time. In the following discussion, to have tractable derivations, we fix the altitude for both the single UAV and multiple UAV scenarios. Note that for both dual-hop and multi-hop settings a similar approach proposed in Algorithm 2 can be used to further adjust the altitude(s) and the horizontal position(s) of the UAV(s) upon having stochastic interference. In the following, we study the position planning for a single UAV and multiple UAVs considering stochastic interference in order.

A. Position Planning for a Single UAV Considering Stochastic Interference

Assuming the altitude of the UAV to be \( h \), let random variable \( I_x \) denote the power of interference at horizontal position \( x = a \) with the corresponding probability density function (pdf) \( f_{I_x}(y) \) and the moment generating function \( M_{I_x}(y) = E(\exp(yI_a)) \). Throughout, we assume that the \( I_x \)'s at different horizontal positions are independent. In this case, the SIR expressions given in (2) will become random variables defined as follows:

\[
SIR_1(x, h) = \frac{p_t}{\eta_{basost}} \frac{\exp(yx^2 + h^2)}{I_x},
\]

\[
SIR_2(x, h) = \frac{p_a}{\eta_{basost}} \frac{(D - x)^2 + h^2}{I_D}.
\]  

As a reasonable extension of (3), we opt to work with the expected value of the SIR expressions:

\[
\begin{align*}
\overline{SIR}_S(x, h) & = \min \{ E(SIR_1(x, h)), E(SIR_2(x, h)) \}, \forall x, h.
\end{align*}
\]

Considering (30), to derive the expected value of the SIR expressions, we first derive the expected value of the inverse of the interference random variable as:

\[
E(\frac{1}{I_x}) = \int_0^\infty \frac{1}{x^2} f_{I_x}(x) dx = \int_0^\infty \frac{1}{x^2} \exp(-yx) f_{I_x}(x) dy dx = \int_0^\infty M_{I_x}(-y) dy.
\]

Define \( \Upsilon_a \triangleq \int_0^\infty M_{I_x}(-y) dy \), whose calculation is deferred to Section VI-C. Then the expected value of the SIR expressions are given by:

\[
E(SIR_1(x, h)) = \frac{p_t}{\eta_{basost}} \frac{\exp(y(x^2 + h^2))}{I_x},
\]

\[
E(SIR_2(x, h)) = \frac{p_a}{\eta_{basost}} \frac{(D - x)^2 + h^2}{I_D}.
\]  

Similar to Lemma 2, it can be verified that \( E(SIR_2(x, h)) \) is a monotone increasing function w.r.t. \( x \), \( x \in (0, D) \). Nevertheless, \( E(SIR_1(x, h)) \) exhibits different behaviors for different moment generating functions. Due to this fact, deriving the analytic optimal solution in this case is intractable. Instead, we propose the following iterative approach to solve the problem. Assume that we need to obtain the position of the UAV to satisfy a given \( SIR_S(x, h) \) denoted by \( \gamma \). Using the \( E(SIR_2(x, h)) \) expression in (33), the corresponding value of \( x \) is the feasible answer, i.e., belonging to \([0, D]\), of the following equation:

\[
\begin{align*}
x &= D - \sqrt{\frac{\Upsilon_{Dp_a}}{\eta_{basost}} - h^2}.
\end{align*}
\]

Using the facts that the expression under the square root should be positive and \( x \) should belong to \([0, D]\), the feasible values of the \( \gamma \) are bounded by:

\[
\frac{\Upsilon_{Dp_a}}{\eta_{basost} (D^2 + h^2)} \leq \gamma \leq \frac{\Upsilon_{Dp_a}}{\eta_{basost} h^2}.
\]

Define \( \gamma_{min} \triangleq \frac{\Upsilon_{Dp_a}}{\eta_{basost} (D^2 + h^2)} \) and \( \gamma_{max} \triangleq \frac{\Upsilon_{Dp_a}}{\eta_{basost} h^2} \). At each iteration, \( i \), of our iterative algorithm described in Algorithm 3, the algorithm derives the horizontal position of the UAV, \( x(i) \), to satisfy a given \( SIR_S \), i.e., \( \gamma(i) \), by solely considering the \( E(SIR_2(x(i), h)) \) using (34). Afterward, it checks the \( SIR_S \) constraint using \( E(SIR_1(x(i), h)) \). If the chosen \( \gamma(i) \) was infeasible, the algorithm decreases the value of the target \( SIR_S \) by a tunable step size \( \epsilon \) for the next iteration. It can be verified that the algorithm converges in at most \( \lfloor (\gamma_{max} - \gamma_{min})/\epsilon \rfloor \) iterations. For the choice of the step size \( \epsilon \) please refer to Remark 2 in the next subsection.

Proposition 2: For sufficiently small values of \( \epsilon \), Algorithm 3 identifies the optimal position of the UAV.

Proof: Please refer to [37].

B. Distributed Position Planning for Multiple UAVs Considering Stochastic Interference

Assuming multiple UAVs as described in Section IV, upon having a stochastic interference, the SIR expressions given by (15) will be random variables described as follows:

\[
\begin{align*}
SIR_1(d, h) &= \frac{p_t}{\eta_{basost}} \frac{\sqrt{d_1^2 + h^2}}{I_{d_1}},
\end{align*}
\]

\[
\begin{align*}
\vdots
\end{align*}
\]

\[
\begin{align*}
SIR_N(d, h) &= \frac{p_a}{\eta_{basost}} \frac{\sqrt{d_N^2}}{I_{\sum_{i=1}^N d_i}},
\end{align*}
\]

\[
\begin{align*}
SIR_{N+1}(d, h) &= \frac{p_a}{\eta_{basost}} \frac{\sqrt{d_{N+1}^2 + h^2}}{I_D}.
\end{align*}
\]  

Note that due to fixed altitude, for a better readability, index \( h \) is omitted from the interference related terms such as \( I \) and later \( \Upsilon \) since the interference is assumed to be measured in that altitude.
In this case,
\[
\text{SIR}_S(d, h) = \min \{ E(\text{SIR}_1(d, h)), \ldots, E(\text{SIR}_{N+1}(d, h)) \}, \forall d, h. \tag{37}
\]
Assume that the random variable \( I_{\sum_{i=1}^{k} d_i} \) follows the distribution \( f_{\sum_{i=1}^{k} d_i}(y) \) with moment generating function \( M_{\sum_{i=1}^{k} d_i}(y) = E(\exp(y I_{\sum_{i=1}^{k} d_i})) \). Considering (32), the expected value of the SIR expressions can be obtained as:
\[
E(\text{SIR}_1(d, h)) = \Upsilon_d \gamma_1 \rho_1 / (\eta_{\text{LoS}} (d_1^2 + h^2)),
\]
\[
E(\text{SIR}_N(d, h)) = \Upsilon_{\sum_{i=1}^{n} d_i} \rho_n / (\eta_{\text{LoS}} d_N^2),
\]
\[
E(\text{SIR}_{N+1}(d, h)) = \Upsilon_D \rho_D / (\eta_{\text{LoS}} (d_{N+1}^2 + h^2)). \tag{38}
\]
In the following, we investigate the two problems pursued in Sections IV-A and IV-B considering the stochastic interference.

**Problem 1: Determining the Minimum Required Number of UAVs and Their Locations to Achieve a Desired SIR \( S \):** Considering (38), upon having non-identical interference distributions along the \( x \)-axis, the SIR expressions can exhibit different behaviors in various horizontal positions. Hence, in general, the exact analysis of this problem is intractable in this case, and thus it can only be solved by exhaustive search, which can be computationally prohibitive. Considering this fact, pursuing a similar approach to Section IV-A, we propose a sub-optimal approach based on maximizing the distances between the UAVs to cover the span between the Tx and the Rx that guarantees achieving the desired SIR \( S \) (\( \gamma \)), and obtains the required number of UAVs and their locations. Note that, in general, the obtained number of UAVs using our approach may not always meet the minimum number of UAVs needed to satisfy the desired SIR \( S \) determined by the exhaustive search. However, we will show in Proposition 3 that these two numbers collide when the interference is i.i.d. along the \( x \)-axis.

Let \( N \) denote the minimum number of needed UAVs, and, correspondingly, \( d_1^* \), \ldots, \( d_N^* \) denote the distances between the UAVs, both of which will later be derived. Let \( D_1 \) denote the set of solutions of \( E(\text{SIR}_1(d, h)) \geq \gamma \) given by:
\[
d_1^2 \gamma - p_u \eta_{\text{LoS}}^{-1} \Upsilon_d h^2 \gamma \leq 0, \quad \forall d_1 \in D_1,
\]
which can be numerically obtained. Note that \( d_1^* \in D_1 \).

Also, the maximum distance between the Rx and UAV \( N \) to satisfy the SIR constraint \( d_{\text{max}} \) is the following closed form expression obtained from solving \( E(\text{SIR}_{N+1}(d, h)) \):
\[
d_{\text{max}} = \sqrt{p_u \eta_{\text{LoS}}^{-1} \Upsilon_D - h^2}. \tag{40}
\]
If \( \exists d_1 \in D : d_{\max} \geq D - d_1 \), using a UAV is enough to achieve the desired SIR \( S \). Otherwise, the position of the middle UAVs, \( d_k^* \), \( 2 \leq k \leq N \), is the largest solution to the following equation:
\[
d_k^* = p_u \eta_{\text{LoS}}^{-1} \Upsilon_{\sum_{i=k}^{N+1} d_i} = 0. \tag{41}
\]
It can be seen that obtaining the distances using the sequence \( d_1^* \rightarrow d_2^* \rightarrow \ldots \) requires solving (41) numerically since \( d_k^* \) appears in the argument of the \( \Upsilon \), which may significantly reduce the speed of computations. Nevertheless, except for \( d_1^* \), all the distances between UAVs can be obtained in a closed form expression by pursuing the following backward approach. Since \( \sum_{i=1}^{k} d_i^* = D - \sum_{i=k+1}^{N+1} d_i^* \), considering \( d_{N+1}^* = d_{\text{max}} \) given by the closed form expression in (40), with replacing \( \sum_{i=k}^{N+1} d_i^* \) by \( D - \sum_{i=k+1}^{N+1} d_i^* \) in (41), we can obtain the position of the middle UAVs in a backward order \( d_{N+1}^* \rightarrow d_N^* \rightarrow d_{N-1}^* \) using the following expression:
\[
d_k^* = \sqrt{p_u \gamma_1 \rho_1 \Upsilon_D - \sum_{i=k+1}^{N+1} d_i^*}, \quad 2 \leq k \leq N. \tag{42}
\]
Finally, the minimum required number of UAVs \( N \) using our approach is given by:
\[
N = \min \{ n \in \mathbb{N} : \exists d_1 \in D : \sum_{k=2}^{n} d_k^* = D - d_1 - d_{\text{max}} \}, \tag{43}
\]
which can be solved similarly to (27). Since for all \( d_{N+1}^* \), where \( d_{N+1}^* \leq d_{\text{max}} \), the SIR constraint at the Rx is met, if the above equation has no solution, its right hand side can be replaced by \( D - d_1 - (d_{\text{max}} - \rho) \), where \( d_{\text{max}} - \rho \geq 0 \) determines the position of the last UAV, i.e., \( d_N^* = d_{\text{max}} - \rho \). Then, starting form \( \rho = 0 \), the problem can be solved assuming small increments in the value of \( \rho \) until a solution is found.

**Proposition 3:** The determined number of UAVs \( N \) using our approach given in (43) coincides with the minimum required number of UAV to satisfy a desired SIR \( S \), when the interference is i.i.d. through the \( x \)-axis.

**Proof:** Please refer to [37].

**Problem 2: Obtaining a Distributed Algorithm to Increase SIR for a Given Number of UAVs in the System:** Considering our methodology in the previous problem and the method described in Section IV-B, we propose Algorithm 4 to increase the SIR \( S \), which only uses message passing between adjacent UAVs to exchange their current location. As can be seen, the proposed algorithm is similar to the proposed algorithm in Subsection IV-B. The only difference is that, instead of

**Algorithm 3:** Iterative Approach to Obtain the Optimal Horizontal Position of the UAV Under the Presence of Stochastic Interference

\begin{algorithm}
\begin{algorithmic}[1]
\State \textbf{input}: Step size \( \epsilon \).
\State Derive the position of the UAV, i.e., \( x^{(s)} \), using (34) with \( \gamma^{(s)} \).
\State if \( E(\text{SIR}_1(x^{(s)}, h)) \leq \gamma^{(s)} \) then
\State \( \gamma^{(s+1)} = \gamma^{(s)} - \epsilon \).
\State if \( \gamma^{(s+1)} \leq \gamma_{\text{min}} \) then
\State Among the previously investigated horizontal positions, fix the UAV at position \( x^{(s')} \), where \( x^{(s')} = \arg \max_{x^{(s')}} \{ E(\text{SIR}_1(x^{(s')}, h)) \} \).
\State \textbf{else}
\State \( i = i + 1 \) and go to line 2.
\State \textbf{end}
\State \textbf{end}
\State \textbf{end}
\State Fix the UAVs at its current position.
\end{algorithmic}
\end{algorithm}
at each horizontal point (see (32)). To concertize the results, in the following, we propose estimating the distribution of the interference power using the Beta distribution, which results in nice close form expressions for the expected value of the SIR expressions.

Any SIR expression given in this section can be written in the following form: $\text{SIR}(x, h) = \frac{S(x, h)}{I_x}$, where $I$ is the power of the signal and $S$ is the power of the interference, which is a random variable. Consider $I_{\text{max}}$ as an upper bound on the power of interference in the environment: $I_x < I_{\text{max}}$, $\forall x \in [0, D]$. In this case, the SIR expressions can be written as:

$$\text{SIR}(x, h) = \frac{S(x, h)}{I_x} = \frac{S(x, h)/I_{\text{max}}}{I_x},$$

(44)

where $I_x \equiv \frac{S(x, h)}{I_{\text{max}}}$ is the normalized interference power. We assume that $I_x \neq 0$, $\forall x$, to avoid undefined SIR expressions. Hence, to model $I_x$, we look for a family of distribution with support on $[0, 1]$, which take the value of zero at 0 and 1. One of the good candidates to do such is the Beta distribution, which is known as a general distribution that can be used to approximate the exponential distribution, Rayleigh distribution, Ricean distribution, and Gamma distribution. In this case, the pdf of $I_x$ is given by:

$$f_{I_x}(x) = \frac{\alpha_x - 1}{B(\alpha_x, \beta_x)} (1-y)\beta_x - 1, \quad (45)$$

where $\alpha_x$ and $\beta_x$ are the shaping parameters of the distribution, $B(\alpha_x, \beta_x) \equiv \Gamma(\alpha_x)\Gamma(\beta_x)/\Gamma(\alpha_x+\beta_x)$, and $\Gamma(.)$ is the gamma function. It can be construed that each point $x \in [0, D]$ is associated with a tuple $\alpha_x, \beta_x$. Some examples of the pdf of the Beta distribution considering different shaping parameters are depicted in Fig. 3. Using the Beta distribution, for $\alpha_x > 1$, we get:

$$E\left(\frac{1}{I_x}\right) = \int_0^1 \frac{1}{y} B(\alpha_x, \beta_x) dy = \frac{1}{B(\alpha_x - 1, \beta_x)} \int_0^1 \frac{1}{y^{\alpha_x - 1}} (1-y)^{\beta_x - 1} dy$$

$$= \frac{1}{B(\alpha_x - 1, \beta_x)} B(\alpha_x - 1, \beta_x) = \frac{\Gamma(\alpha_x - 1)\Gamma(\beta_x)}{\Gamma(\alpha_x + \beta_x - 1)} = \frac{\Gamma(\alpha_x - 1)}{\Gamma(\alpha_x + \beta_x - 1)} = \frac{\alpha_x + \beta_x - 1}{\alpha_x - 1}, \quad (46)$$

where the first equality on the last line is the result of the gamma function property $\Gamma(z + 1) = z\Gamma(z)$. As compared to (32), the above result eliminates the need for calculation of the moment generating function of the interference power and its integral at each point. As a result, a new set of nice close form expressions can be obtained by putting $\gamma = \frac{\alpha_x + \beta_x - 1}{\alpha_x - 1}$ in (34), (35), (39), (40), (42). Due to space limitations, we avoid writing the corresponding expressions.

\textbf{Algorithm 4: Distributed Position Planning for Multiple UAVs Upon Having Stochastic Interference}

\begin{verbatim}
input : Step size $\epsilon$
1 $i = 0$, $d_N^{(0)} = 0$
2 $\gamma^{(i)} = E(SIR_{\text{Rx}}(d^{(i)}, h)) = \frac{p_{\text{x}}P_G}{d_{\text{Rx}}^{(i)^2}} T_D$
3 Given $d_{N+1}^{(i)}$ and $\gamma^{(i)}$, obtain $d_{N+1}^{(i)} \rightarrow d_{N+1}^{(i-1)} \rightarrow \cdots \rightarrow d_1^{(i)}$ in order using backward propagation based on (42).
4 Send a message from Tx to UAV$_1$ and measure SIR$_1$
5 if SIR$_1 < \gamma^{(i)}$ then
6 $\gamma^{(i+1)} = \gamma^{(i)} - \epsilon$
7 $i = i + 1$ and go to line 2.
8 else
9 Fix the UAVs at their current positions.
10 end
\end{verbatim}

forward propagation, Algorithm 4 uses \textit{backward propagation}, by which each UAV transmits its position to the adjacent UAV located toward the Tx, which is used to exploit the closed form expression given by (42). Consequently, to examine the satisfaction of the targeted SIR, the average value of the SIR at the first UAV is measured. Similar to Algorithm 1, Algorithm 4 converges in at most $\gamma^{(i)}/\epsilon$ iterations, and its worst computational complexity is $O(\gamma^{(i)}/\epsilon)$ at each UAV. In the following, we obtain the performance guarantee of our proposed algorithm for both i.i.d. and non-i.i.d interference through the horizontal axis.

\textbf{Proposition 4:} For any given number of UAVs and a sufficiently small step size $\epsilon$, assuming the same altitudes for the UAVs, if $I_x$s are i.i.d. for $x \in [0, D]$, then Algorithm 4 is guaranteed to converge to the maximum achievable value of SIRs.

\textbf{Proof:} Please refer to [37].

\textbf{Proposition 5:} For a given number of UAVs, a sufficiently small step size $\epsilon$, assuming the same altitudes for the UAVs, if $I_x$s are non-i.i.d. for $x \in [0, D]$, then Algorithm 4 is guaranteed to converge to the maximum value of sequence $\gamma^{(i)}$, $\gamma^{(0)}$, $\gamma^{00}$, where $\gamma^{(i)} = \gamma^{(0)} - \epsilon \times i$, for the target SIR, for which covering the distance between the Tx and the Rx using backward propagation and maximum separation among the UAVs obtained in (42) is feasible.

\textbf{Proof:} Please refer to [37].

\textbf{Remark 2:} For Algorithm 1, for a given step size $\epsilon$, we have $\text{SIR}_S - \text{SIR}_S \leq \epsilon$, where $\text{SIR}_S$ is the optimal solution of the problem and $\text{SIR}_S$ is the achieved SIR of the algorithm. The same bound holds for Algorithms 3 and 4 by replacing $\text{SIR}_S$ with $\text{SIR}_S$ and $\text{SIR}_S$ with $\text{SIR}_S$ upon having i.i.d interference through x-axis. These bounds can be used as a guideline to tune the step sizes of the algorithms considering the tolerable deviation from the optimal solution. Note that, in general, a smaller step size results in a longer convergence time and a smaller final error.

\subsection*{C. Discussion on the Moment Generating Function of the Interference}

So far, all the expressions derived in this section can be applied to any given distribution of the interference power by obtaining the moment generating function and its integral.
VII. NUMERICAL RESULTS

The simulation parameters are summarized in Table II. The general simulation parameters shown in the first sub-table of Table II are chosen by following [25], also we set $\eta_{\text{LoS}} = \mu_{\text{LoS}}$.

A. Dual-Hop Setting

Considering the transmission power of the UAV and the distance between the Tx and Rx as given in the second sub-table of Table II, Fig. 4 depicts the locus described in Lemma 1 for various parameters. Considering the solid black line and the dotted red line as the references, as expected, increasing $p_t$ (the marked blue and dashed magenta lines) shifts the locus toward the Rx. Also, considering the dotted red line and the dashed magenta line as the references, bringing the MSI closer to the Tx/Rx (the solid black and marked blue lines) shifts the locus downward, which is equivalent to a decrease in the required UAV altitude.

Fig. 5 compares the SIR of the system obtained using Theorem 1 to both the random placement, the performance of which is obtained by randomly placing the UAV in 1000 Monte-Carlo iterations, and the method described in [25], which does not capture the existence of the MSI (see Section I). In this simulation, it is assumed that the altitude of the UAV changes in the interval [10m, 50m] and the simulation is conducted for two realizations of $p_t$ and $p_u$ described in the figure. The rest of the parameters are described in the third sub-table of Table II. As can be seen, the difference between the performance of our approach and the baselines is more prominent in low altitudes (up to 65% increase in SIR$_S$). Also, on average, our method leads to 30.14% and 25.73% increase in SIR$_S$ as compared to the random placement and the method of [25], respectively.

B. Multi-Hop Setting

Considering the parameters described in the fourth sub-table of Table II, based on (27), the minimum required number of UAVs to satisfy different values of SIR$_S$ when $p_u = 1W$ for multiple MSI positions (when $X_{\text{MSI}} = 500m$, $Y_{\text{MSI}} = 400m$ for multiple $p_u$ values) is depicted in Fig. 6 (Fig. 7). From Fig. 6, it can be observed that as the MSI gets closer to the Tx/Rx the minimum number of needed UAVs decreases significantly. Fig. 7 illustrates the performance of our approach and the baselines is more prominent in low altitudes (up to 65% increase in SIR$_S$). Also, on average, our method leads to 30.14% and 25.73% increase in SIR$_S$ as compared to the random placement and the method of [25], respectively.
the required number of UAVs increases. Also, from Fig. 7, it can be seen that by increasing the $p_u$ the required number of UAVs decreases.

Considering the parameters described in the fifth sub-table of Table II, $d_{min} = 4m$, and $\epsilon = 0.1$, Fig. 8 depicts the performance of our distributed algorithm (Algorithm 1) for various number of UAVs in the network. From Fig. 8, it can be seen that as the number of UAVs increases our algorithm achieves larger values of SIR$_S$ with a faster convergence speed. The faster convergence is due to the larger coverage length when having a large number of UAVs. Fig. 9 reveals the significant increase in the SIR$_S$ obtained through comparing the achieved SIR$_S$ using our distributed algorithm with both the method described in [25] and the random placement, the performance of which is obtained by randomly placing the UAVs in 1000 Monte-Carlo iterations.

Position planning upon having stochastic interference leads to similar results as compared to the previous performed simulations, especially upon having i.i.d. interference along x-axis. As an example, considering the parameters of the previous simulation, Fig. 10 depicts the performance of our distributed algorithm (Algorithm 4) with different number of UAVs in the network. We assume that the interference follows the Beta distribution (see Section VI-C). We first consider the interference to be non-i.i.d. through the x-axis, where $\alpha_x$ and $\beta_x$ are chosen such that $\alpha_x/\beta_x = 0.8A$, $\forall x \in [0, D]$, is depicted in the bottom subplot of Fig. 10. Comparing the two subplots, upon having the non-i.i.d. interference, moving from one iteration to the next may not lead to a better SIR$_S$ due to the unpredictable power of interference at different positions during the iterations (see (42)); however, in both cases, the convergence is achieved through a few iterations. Also, comparing the performance of our algorithm with the baselines will result in similar results depicted in Fig. 9, which is omitted to avoid redundancy.

C. Adjusting the Altitudes and the Horizontal Positions of the UAVs

We first conduct a set of simulations to demonstrate the effect of the altitudes of the UAVs on the performance of Algorithm 1, when the UAVs have the same altitude. The results are depicted in Fig. 11 assuming the number of UAVs $N = 50$. We use the same simulation parameters as in Figs. 8 and 9 except the value for $Y_{MSI}$, which is variable. As can be seen, as the MSI gets closer to the UAVs (smaller values of $Y_{MSI}$), the altitude that results in the best performance increases. However, increasing the altitude after a certain value results in performance reduction. This is because increasing the altitude initially results in decreasing the effect of interference on the UAVs; however, after a
certain point the link from the Tx to the first UAV and from the last UAV to the Rx become the bottleneck and increasing the altitude leads to a reduction in the SIR $S$.

To demonstrate the effect of adjustments of the altitudes and the horizontal positions of the UAVs on the SIR $S$ using Algorithm 2, we fix the location of MSI at $X_{\text{MSI}} = 500m$, $Y_{\text{MSI}} = 150m$ and choose the corresponding altitude that results in the best performance of Algorithm 1 from the red curve with circle markers in Fig. 11, i.e., $h = 220m$, as the initial altitude of all the UAVs. Also, the initial horizontal positions of the UAVs are obtained using Algorithm 1. Fig. 12 depicts the location of the Tx, the MSI, the Rx, and the UAVs in the 2-D plane for different number of iterations of Algorithm 2. Two key observations from Fig. 12 are as follows: i) the algorithm brings the first few UAVs closer to the Tx, the last few UAVs closer to the Rx, while moving the middle UAVs away from the MSI; ii) the algorithm leads to larger horizontal separations between the first few and the last few UAVs, while the middle UAVs are closer. The reason behind these observations is that the effect of interference on the middle UAVs is larger since they are closer to the MSI; and thus the algorithm brings them closer to each other and moves them away from the MSI. Note that these observations and the semicircle 2-D shape of the UAVs configuration in Fig. 12 are parameter specific and may vary for a different parameter setting, e.g., a different location for the MSI. Fig. 13 depicts the increase in SIR $S$ achieved using Algorithm 2, where 25% increase in SIR $S$ can be observed.

**VIII. Conclusion**

In this work, we studied the UAV-assisted relay wireless communication paradigm considering the presence of interference in the environment. We investigated the UAV(s) position planning considering two scenarios: i) existence of an MSI, and ii) existence of stochastic interference. For each scenario, we first endeavored to maximize the (average) SIR of the system considering a single UAV in the network. Afterward, for each scenario, we studied the position planning in the multi-hop relay scheme, in which the utilization of multiple UAVs is feasible. To this end, we first proposed a theoretical approach, which simultaneously determines the minimum number of needed UAVs and their optimal positions so as to satisfy a desired (average) SIR of the system. Second, for a given number of UAVs in the network, we proposed a distributed algorithm along with its performance guarantee, which solely requires message exchange between the adjacent UAVs so as to maximize the (average) SIR of the system. Furthermore, we illustrated the performance of our methods through numerical simulations. The methodology of this work can inspire multiple future works revisiting the previously studied problems in the context of UAV-assisted relay wireless communications considering the existence of interference in the environment. Also, investigating the studied problems in this paper upon having multiple pairs of Tx and Rx is a promising future work.

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