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RESEARCH ARTICLE

Energy-Efficient Power-Controlled Resource Allocation for MIMO-Based Cognitive-Enabled B5G/6G Indoor-Flying Networks

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ABSTRACT The proliferation of unmanned aerial vehicles (UAV), i.e., drones, in communication systems has recently attracted both industry and academia. This is mainly due to their flexible capabilities and features, which can support a wide range of communication applications. More specifically, drones can offer better coverage, better capacity, and a many-fold quality-of-service enhancement. Accordingly, recent communication technologies have been integrated with drones to support the unprecedented communication requirements of beyond fifth-generation (B5G) and 6G networks. Upon these bases, this paper sought to investigate the potential capabilities of multi-antenna drones in an uplink transmission cognitive radio (CR) indoor environment. With such an integrated system, a set of multiple-antenna drones communicates with a CR BS through the opportunistic utilization of the available channels without affecting the primary user's activities. In particular, this paper proposes an adaptive power channel assignment (APCA) protocol that aims to minimize the per-drone transmit power under a set of relevant CR-related and quality-of-service constraints. The constraints include the minimum rate requirements, the probability of success, per-antenna power, the minimum SNR, and relevant CR-related constraints. Furthermore, this paper attempts to mathematically prove that the formulated optimization problem is convex, thus, the optimal solution can be attained. Accordingly, the conventional convex algorithms are adopted to solve the problem and obtain the solution. The proposed APCA protocol is capable of selecting the channel that requires the minimum power. To investigate the performance of the proposed APCA protocol, we compare its performance against that of the conventional equal-power allocation. Simulation results reveal that the proposed APCA protocol significantly improves system performance in terms of the overall transmit power.

INDEX TERMS UAVs, indoor propagation, cognitive radio, power-allocation, channel assignment, convex-optimization.

I. INTRODUCTION

Unmanned aerial vehicles (UAV) platforms have been recently configured as potential candidates to support a wide range of daily life services and applications [1], [2]. More specifically, due to their ease of deployment, high mobility, low maintenance cost, and ability to hover, UAV platforms, i.e., drones, can support a large set of civilian and military applications, including navigation, control, and reconnaissance [3]. Accordingly, recent research efforts have

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promoted drones to play a key role in the advances of supporting wide-scale beyond fifth-generation (B5G) networking. In fact, this is due to the drones' abilities to cover hard-to-reach areas as well as crowded hot spots through initiating line-of-sight (LoS) communication, especially for cell-edge users [4], [5]. Accordingly, current research directions are focusing on the integration of drones with the proposed B5G architecture. This integration offers a considerable improvement on the quality-of-service (QoS). However, it is important to note that such integrated approaches require addressing several new design challenges, including those related to the communication protocols, deployment strategies, and developing appropriate resource allocation techniques that are capable to support the QoS requirements. In particular, B5G/6G networks should be able to offer reliable and energy-efficient communication services with high data rates while supporting a massive number of users [6]. Over the past few years, several techniques have been proposed and investigated to support these unprecedented requirements. The proposed techniques include multiple antennas techniques [7], cognitive radio (CR) [8], non-orthogonal multiple access (NOMA) [9], and Millimeter-Wave communications [10]. To be specific, the multiple antennas technique, such as multiple-input multiple-output (MIMO), is implemented to increase spectral efficiency by transmitting and receiving multiple data streams over the same time-frequency resources, which as a result facilitating the signal processing process, decreasing the transmit power, and mitigating small-scale fading [11], [12]. On the other hand, CR technology has been also considered as a potential solution to enable the efficient and opportunistic spectrum's utilization by the unlicensed users, i.e., secondary users (SUs), while maintaining the primary user (PU) activities without any interruption [13], [14]. This can be achieved by assuming that the CR network (CRN) can sense the surrounding radio frequency environment and select the operating channels that do not interfere with the licensed PU networks. To this end, it has been widely agreed that there is no stand-alone technology that can individually support all the B5G requirements [15], [16]. Therefore, the integration between technologies has been recognized as a potential solution for addressing the requirements of future wireless communication systems [17].

A. MOTIVATION

Due to the vital importance of employing UAVs in indoor communication applications, such as providing security solutions, societal safety, indoor healthcare administration, and extended high-speed coverage in crowded indoor spaces (e.g., shopping malls), this paper considers the uplink transmission of MIMO-based cognitive-enabled B5G/6G indoor-flying networks. In addition, due to UAVs' size and their limited battery capacity, the power consumption of UAVs affects not only the flying time but also the potential capabilities of UAVs in future wireless communication systems. Therefore, energy-efficient protocols are needed to meet the exponential growth in the deployment of UAVs in communication systems. Specifically, developing power-aware communication protocols and strategies poses an important challenge in enabling efficient UAV deployment. Accordingly, this paper proposes a power minimization framework for a MIMO-based CR-enabled B5G/6G indoor-flying network. This framework aims to minimize the overall transmit power of each UAV while satisfying a set of QoS requirements.

B. CONTRIBUTION

In this paper, we consider an uplink indoor UAV-based system that employs CR technology with MIMO, which is referred to as a MIMO-based CR-enabled indoor-flying network throughout this paper. With such integrated system, a set of multi-antenna drones aims to transmit data for a CR BS (BS) over a set of idle channels. The applications of such an indoor environment include those related to the controlling of manufacturing industry, indoor monitoring, and greenhouse applications [18], [19]. In particular, we develop a joint power minimization and channel assignment framework aiming to minimize the per-drone transmit power while satisfying a set of relevant QoS and CR constraints. We summarize the main contributions of this paper as follows: Firstly, we characterize the uplink transmission of an indoor MIMO-CR UAV-based system. Next, we formulate the problem of the power-controlled channel assignment. To be specific, Unlike most of the previous research in the literature, the proposed approach in this paper considers the per-antenna power constraints for each drone [20], [21]. The formulated optimization framework is shown to be a convex one, which as a result, can be optimally solved using standard polynomial-time methods. Accordingly, considering the computed power levels over the different idle channels, each drone selects the channel that achieves the minimum required power. We conduct simulation experiments to evaluate the performance of our proposed protocol compared to a benchmark approach, namely the equal-power allocation approach.

C. RELATED WORK

Recently, several research works have investigated the potential capabilities of combining drones with recent communication systems. For example, an CR UAV-based system with single-antenna approach has been discussed in [22] and [23]. More precisely, the authors in [22] have discussed the energy management for UAV-enabled CR system, where an optimization framework that aims to maximize the number of transmitted bits is developed. Furthermore, the secure communication of a single-input single-output (SISO) CR UAV-based system has been discussed in [23], where the achieved rates by the CR users are maximized by robustly optimizing the UAV's trajectory and transmitting power. On the other hand, the authors in [24] have investigated the joint UAV trajectory and power allocation optimization for NOMA protocol in CR network, where it has been assumed that a UAV node transmits data streams to multiple SUs by using of NOMA protocol under the interference constraint to the PU. In order to maximize the sum rate of all SUs, the UAV trajectory as well as the total transmission power and the power allocation scheme for NOMA are carefully designed.

Additionally, other research efforts have been conducted for MIMO-CR UAV-based systems. For example, an uplink MIMO-CR UAV-based system has been considered in [24], where closed-form expressions of the optimal PU and SU transmit power levels for space alignment relay-assisted scenario have been derived. Furthermore, the work in [25] has considered a CR-MIMO networks for mmWave waves, where sum-rate maximization problem has been considered under a per-user minimum rate constraint. On the other hand, the work in [26] has assumed that a multi-antenna UAV acts as BS, where the lens on the UAV are utilized as a transmission array. To end with, a single multi-antenna UAV system communicating with two users has been investigated in [27], where the Ricean fading model with LoS and non-LoS (NLoS) links were considered. With this, the beamforming vectors that maximize the achievable ergodic sum-rate are evaluated. In particular, the sub-optimal beamforming pre-encoder with the knowledge of CSI at the UAV's transceivers was proposed.

D. PAPER ORGANIZATION

The rest of the paper is structured as follows. Section II presents the network model, characterizes the indoor channel propagation, and describes the MIMO-based network capacity analysis. In Section III, the problem statement and QoS constraints are introduced. Section IV develops power-minimization and channel assignment frameworks, and provides the proposed APCA protocol. Section V provides a set of simulation results to validate the proposed system. Finally, Section VI concludes the paper.

II. NETWORK AND PROPAGATION MODELS

A. NETWORK MODEL

In this paper, we consider an uplink MIMO CR-based UAV-based indoor system, in which a set of multi-antenna CR-capable drones communicates with a CR multi-antenna ground BS. Each UAV is equipped with N uncorrelated antennas, where it is also assumed that the noise is uncorrelated across the receiver's antennas [28]. The CR-enabled drones coexist with several licensed PU networks (PRNs), each with its own licensed spectrum and carrier frequency. Let $\mathcal{M}$ represent the set of all PR channels, where $\mathcal{M} = \{1, 2, \cdots, M\}$, and M is the number of the available channels. The communications between the drones and the BS are coordinated over a common control channel (CCC). The competing drones access the available spectrum through a CSMA/CA-based protocol with control packet handshaking, which is implemented over the CCC. The status of each PU channel is modeled using a two-state BUSY/IDLE alternating renewal process, where the 'BUSY' state indicates that the channel is not available for CR communications, while the 'IDLE' state indicates that the channel can be utilized by the drones using the federal communications commission (FCC) maximum allowable power limit ($P^{(i)}_{max}$) [28]. Accordingly, each CR user, i.e., drone, can sense the channel usage of the different PU channels. We assume the channel usage pattern over each channel slowly changes with time, and drones can obtain the PU spectrum usage pattern by conducting cooperative spectrum sensing with neighboring CR devices. In CR operating environment, transmission reliability is a very challenging task because of the PU activities and fading conditions. Thus, it is essential in CR-based communications to provide network availability guarantees in terms of packet success performance. Thus, we consider that a given data packet transmission can proceed over a given channel i only if the success probability over that channel is greater than a predefined probability of success threshold, determined by the application layer. Fig. 1 shows an illustrative example of a network model of multiple-antenna drones communicating with a multi-antenna CR BS within an indoor environment, i.e., a shopping mall.

B. INDOOR PROPAGATION MODEL

To investigate the performance of our proposed UAV-based MIMO communication system, it is crucial to characterize the corresponding indoor channel propagation. In fact, the indoor environments are typically characterized by their relatively limited space, high obstacle density, and dynamic user behavior. These considerations limit the UAVs' flight altitude, flight speed, and distance toward the ceiling, objects, and possibly other UAVs. Specifically, in such an in-door operating environment, the UAV flies at a relatively low altitude (within 2 to 3 meters from the ceiling) at a height of a few meters with a relatively low speed to avoid accidents and result in minimal disturbance to users. In general, rotary-wing UAVs are more suitable for the indoor environment as they can hover in the air with zero speed [29]. Such unique characteristics of drones' operating indoor environments, directly impact the LoS probability and multi-path components. Specifically, the mobility of drones influences Doppler spread. However, Doppler is very small for hovering drones because of the relatively limited indoor space, which usually limits the drone's speed and motion. In the considered network model, we assume that the UAVs hover at a relatively low speed, resulting in negligible impacts of Doppler spread on communication performance. With such limited Doppler spread and noting that the BS in our network model is statically mounted at or near the ceiling (i.e., fixed location), the uplink channel between the UAVs and BS can be modeled using a rich scattering channel model with an LoS. We note that several studies have been carried out to provide accurate propagation models for rich scattered indoor/small-world environments (e.g., [30], [31]). In fact, for a wide range of frequencies, the presented indoor channel models in [30], [31] have been demonstrated as adequate propagation models for indoor communications with LoS and NLoS components. In our work, we adopt the rich scattered with LoS

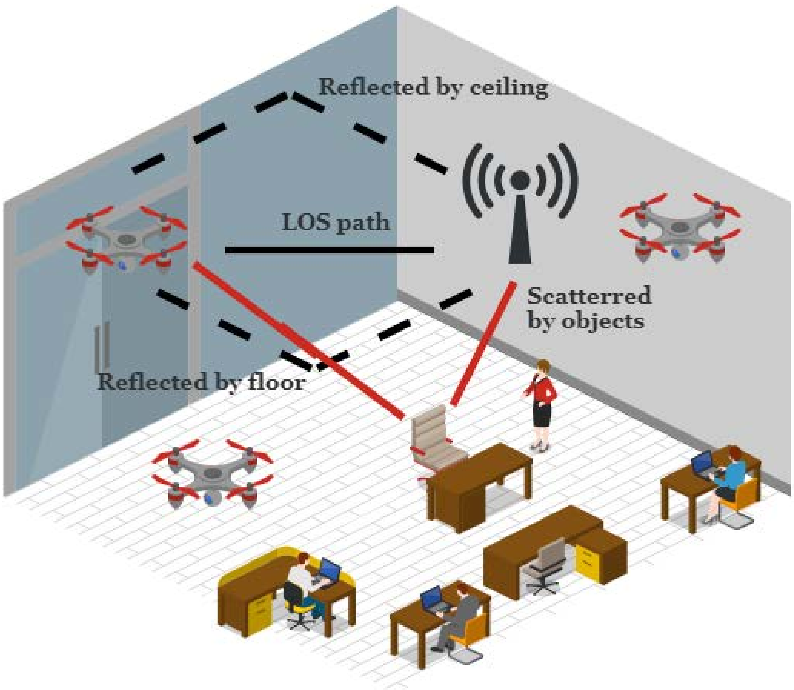


FIGURE 1. A network of drones in an indoor environment.

indoor propagation model presented in [30] to characterise the uplink channel between the communicating drones and the BS. In specific, the path loss in the indoor environment, i.e., the shopping mall environment, is estimated based on the close-in free space (CIF) reference distance model, where the frequency-weighted path loss exponent is given as [30]:

$$\zeta[dB] = FSPL(f, 1m) + 10n(1 + b(\frac{f - f_0}{f_0}))\log_2(\frac{d}{1m}) + X_\sigma^{CIF}, \quad (1)$$

where b is an optimized parameter that captures the slope of the drone, d is the distance between the communicating drones (in meters), X_σ^{CIF} is the shadow fading with σ in dB, and n is the path loss exponent and FSPL is the free space path-loss at a distance of 1 m with carrier frequency f. In fact, FSPL can be evaluated as,

$$FSPL(f, 1m) = 20\log_{10}(\frac{4\pi f}{c}), \quad (2)$$

where c is the speed of light, f_0 is a fixed frequency point (a reference for all frequencies). The term f_0 can be computed as,

$$f_0 = \frac{\sum_{k=1}^{K} f_k N_k}{\sum_{k=1}^{K} N_k}, \quad (3)$$

where K is the number of unique carrier frequencies in the band, and N_k is the number of path loss data points associated with the kth frequency (f_k). Because of the limited impact of drones' mobility on Doppler spread due to their relatively slow mobility and fixed receiver (BS) location, the described indoor propagation model in this section [30] can be used to characterise the uplink channel between the drones and the BS in our work.

C. MIMO CHANNEL MODEL, ACHIEVED CAPACITY, AND SUCCESS PROBABILITY

The MIMO channel for a system with $N \times M$ antennas is typically characterized by the channel matrix H. The rank of the matrix H, denoted by $r \leq \min(N, M)$, characterizes the achieved capacity of the system [32]. In fact, if the rank of H is r, the system is equivalent to r parallel channels. In this case, the MIMO capacity can be viewed as the capacity of r parallel single-input single-output (SISO) channels, where the channel gains are related to the Eigenvalues of HH^H. Specifically, the MIMO capacity can be reduced to the achieved capacity of r parallel channels. It has been shown that when the MIMO channel is set up such that each eigen-channel of H is independent ($r = N$), the capacity gains can be made linear [32]. Recall that in our system model, we consider an indoor UAV communication environment with limited Doppler spread (due to the relatively low UAV speed and fixed receiver location) and rich scattering environment with LoS components. Under this operating environment and by implementing a proper antenna placing similar to the ones proposed in [33], [34], and [35], each eigen-channel of H becomes independent, resulting in uncorrelated MIMO channels (i.e., H is full rank with $r = N$). Thus, each pair of transmit-receive antennas provides a signal path from the UAV to the BS as demonstrated in [36], [37], and [38]. Thus, each drone can transmit N independent data streams to the BS, in which the achieved data rate over the N antennas for that drone on a given channel i can be computed as

$$R^{(i)} = \sum_{j=1}^{N} R_j^{(i)}. \tag{4}$$

where $R_j^{(i)} = W \log_2 (1 + \alpha_j^{(i)} P_j^{(i)})$ denotes the achieved data rate on antenna j over channel i at the BS, W is the channel bandwidth, $\alpha_j^{(i)} = \frac{\zeta_j^{(i)}}{N_o}$ is the normalized channel power gain, and $P_j^{(i)}$ is the allocated power to antenna j over channel i.

A CR drone transmission is said to be successful over a selected channel i if-and-only the needed transmission time is less than the selected channel availability time. It is worth noting that in CR-based networks, the impact of decoding errors on the success probability performance can be significantly mitigated by implementing efficient error correction mechanisms at the CR users [39]. By mitigating the impact of decoding errors, a CR data packet transmission is considered to be successful over a selected channel i if there is no collision with the uncontrollable PU activities. The feasibility of this consideration has been demonstrated in several previous works [39], [40]. Accordingly, for a packet of length D and transmission rate of $R^{(i)}$, the required transmission time over each channel i can be determined as $t_x{}^{(i)} = D/R^{(i)}$. Given that the BUSY and IDLE periods over the i PU channel are exponentially distributed random variables, the probability of packet success over channel i for CRNs has been derived in several previous works (e.g., [39], [40]) as:

$$P_s^{(i)} = e^{-\frac{D}{R^{(i)}\mu_i}}. \tag{5}$$

III. PROBLEM DEFINITION AND QoS CONSTRAINTS

Assuming a given drone, namely A, wishes to transmit to the CR BS. Accordingly, it senses the CCC first in order to search for the set of the idle channels. When the CCC is sensed idle, the drone A competes to access the CCC using a CSMA/CA-based protocol. Upon accessing the CCC, the drone A and the BS exchange the needed control packets to agree on the operating channel and transmit power levels). Specifically, for the uplink communication between the drone A and the ground CR BS, the set of idle channels, the set of available antennas per drone, the CSI over each antenna-channel combination between the drone A and the CR BS, our objective is to find the appropriate channel assignment that requires the minimum possible total transmit power while achieving a set of relevant QoS and CR-related constraints. Such constraints include:

C1. QoS constraint: The drone A should achieve a minimum required rate demand (R_D) over the i^{th} channel, $\forall i \in \mathcal{M}$. This constrain can be mathematically written as,

$$R^{(i)} = \sum_{j=1}^{N} W \log_2(1 + \alpha_j^{(i)} P_j^{(i)}) \geq R_D.$$

C2. Total power constraint: The allocated power for the different antennas over the selected channel i should not exceed the maximum allowable total transmit power over that channel (P_{total}). This constrain can be mathematically written as,

$$\sum_{j=1}^{N} P_j^{(i)} \leq P_{total}$$

C3. Per-antenna constraint: The allocated power for each antenna over the selected channel i should not exceed the maximum per-antenna power P_{per}. This constrain can be mathematically written as:

$$P_j^{(i)} \leq P_{per},\ j = \{1, \ldots, N\}, \quad \forall i.$$

C4. Probability of success constraint: The probability of successfully transmission over the selected channel i should be greater than a threshold value γ, where γ is application dependant. This constrain can be mathematically written as,

$$P_s^{(i)} \geq \gamma^*.$$

C5. Per-antenna SNR constraint: The received SNR at antenna j over the selected channel i between A and the BS should be greater than a pre-defined SNR threshold of μ^*. This constrain can be mathematically written as:

$$\mathrm{SNR}_j^{(i)} \geq \mu^*,\ j = \{1, \ldots N\}.$$

IV. THE PROPOSED POWER-MINIMIZATION AND CHANNEL ASSIGNMENT ALGORITHM

To explore the potential capabilities of the considered MIMO-CR UAV-based system, we develop a power-minimization framework and channel assignment approach that aim to select the operating channel that requires the minimum total transmit power for each drone while satisfying the aforementioned set of relevant QoS and CR-related constraints. To be specific, we determine the per-antenna power allocation for each drone that results on minimizing the overall needed transmit power over each idle channel $i \in \mathcal{M}'$. Then, the output of the first stage is used to select the operating channel i^* that requires the minimum needed overall transmit power.

A. THE POWER MINIMIZATION PHASE: FORMULATION AND SOLUTION

As mentioned before, to select the appropriate channel assignment, the minimum required transmit power for each drone over all idle channels $i \in \mathcal{M}'$ needs to be firstly computed. The objective function can be mathematically written as $\min_{P_j^{(i)}} \sum_{j=1}^{N} P_j^{(i)}$.

Given the mathematical presentations of the objective function and the designed constraints in **C1** to **C5**, the power-minimization problem over a given idle channel i can be mathematically written as:

$$\min_{P_j^{(i)},\ \forall i} \sum_{j=1}^{N} P_j^{(i)} \tag{6a}$$

$$\text{s. t.} \sum_{j=1}^{N} W \log_2(1+\alpha_j^{(i)} P_j^{(i)}) \geq R_D, \tag{6b}$$

$$\sum_{j=1}^{N} P_j^{(i)} \leq P_{total}, \tag{6c}$$

$$P_j^{(i)} \leq P_{per}, \quad j = \{1, \ldots N\}, \tag{6d}$$

$$P_s^{(i)} \geq \gamma^*, \tag{6e}$$

$$\text{SNR}_j^{(i)} \geq \mu^*, \quad j = \{1, \ldots N\}. \tag{6f}$$

It is worth pointing out that the constraint in (6e) can be re-written as a function of the achieved rate, such that $R_j^{(i)} \geq \dfrac{D}{\mu_j \ln \gamma^*}$. Accordingly, the constraints (6b) and (6e) can be combined into a single constrain as follows:

$$\sum_{j=1}^{N} W \log_2(1+\alpha^{(i)} P_j^{(i)}) \geq R_i^*,$$

where $R_i^* = \max(R_D, \dfrac{D}{\mu_j \ln \gamma^*})$. The SNR on antenna i over channel j is $SNR_j^{(i)} = P_j^{(i)} * \alpha_j^{(i)}$ and the minimum SNR on antenna j over channel i is $\mu^* = P_{THR}^{(i)}(j) * \alpha_j^{(i)}$. With this, the constraint (6f) can be written in terms of $P_j^{(i)}$ as,

$$P_j^{(i)} \geq P_{THR}^{(i)}(j),\ j = \{1, \ldots N\}.$$

Accordingly, the power minimization problem in (6) can be re-written as follows:

$$\begin{aligned} \min & \sum_{j=1}^{N} P_j^{(i)} \\ \text{s.t.} & \sum_{j=1}^{N} W \log_2(1+\alpha^{(i)} P_j^{(i)}) \geq R_i^*, \\ & \sum_{j=1}^{N} P_j^{(i)} \leq P_{total}, \\ & P_{THR}^{(i)}(j) \leq P_j^{(i)} \leq P_{per}, \quad j = \{1, \ldots N\}. \end{aligned} \tag{7}$$

Lemma 1: The optimization problem in (7) is a convex optimization problem that can be optimally solved in polynomial-time using standard convex optimization techniques.

Proof: We note that the objective function is an affine function in terms of $P_j^{(i)}$, which is convex. In addition, the second and third constraints are also linear constraints in terms of $P_j^{(i)}$, which is considered an affine concave function. Now, we prove that the first constraint is also convex. We define this constraint as:

$$f(P_j^{(i)}) = \sum_{j=1}^{N} W \log_2(1+\alpha^{(i)} P_j^{(i)}) - R_i^*$$

To check the convexity of $f(P_j^{(i)})$, we compute the corresponding Hessian matrix $H_f(P_j^{(i)}) = \nabla^2 f(P_j^{(i)})$, which is given in (8), as shown at the bottom of the next page. It is clear that all Eigenvalues of $\mathbf{H}_f(P_j^{(i)})$ are negative, and hence H_f is negative semidefinite. Thus, the function $f(P_j^{(i)})$ is concave. Since the objective function and constraints are convex, our problem is convex. This means that it can be optimally solved using standard convex optimization methods to determine whether the problem is feasible (i.e., channel i can be used for the drone to BS communication) or the problem is infeasible (the channel cannot be used for the drone to BS communication).

Observation: Due to the non-decreasing nature of the achieved rate with the transmit power, the equality in the first constraint in (7) always holds, and thus, the optimal solution can be found. This has been proved by contradiction in [41] (Section III.B). This is because the lowest transmit power

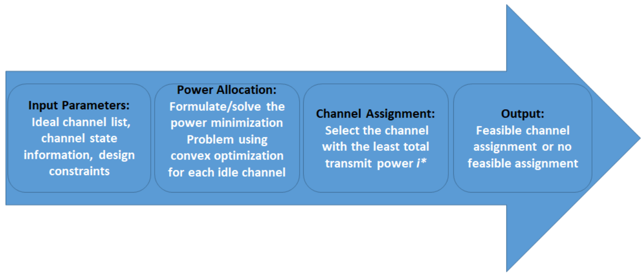


FIGURE 2. **The block diagram of the proposed APCA protocol.**

Algorithm 1 The Proposed APCA Protocol

Input: Ideal channel list $\mathcal{M}'$, N, R_i^*, γ, P_{per}, W, the channel power gain $\alpha_j^{(i)}$
Let $\mathcal{M}'' = \Phi$
for $i = 1 : \mathcal{M}'$ **do**
  Solve (7) for $P_j^{(i)}$ using standard convex optimization methods
  if (7) is feasible
    $\mathcal{M}'' \Longleftrightarrow \mathcal{M}'' + \{i\}$
    $P_R^{(i)} \Longleftrightarrow \sum_{j=1}^{N} P_j^{(i)}$
  end if
end for
if $\mathcal{M}'' \neq \Phi$
  $i^* = \arg\min_{i \in \mathcal{M}''} \left\{P_R^{(i)}\right\}$
  Output: feasible assignment i^*, $P_j^{(i^*)}$, $P_R^{(i^*)}$
else
  Output: no feasible assignment
end if

levels that satisfy our power-minimization objective are the ones that result in a total data rate equal to the demand rate.

B. THE CHANNEL ASSIGNMENT PHASE

To compute the optimal channel assignment that minimizes the overall transmit power, the power-minimization problem in (6) is solved for each idle channel $i \in \mathcal{M}'$. If the power-minimization problem is feasible for channel i, this channel is added to a feasible channel list $\mathcal{M}''$. Then, the computed feasible per-antenna transmit powers, $P_j^{(i)}, j \in N$, are used to compute the needed total transmit power over channel i ($P_R^{(i)}$) as:

$$P_R^{(i)} = \sum_{j=1}^{N} P_j^{(i)}. \tag{9}$$

Given $P_R^{(i)}$, $\forall i \in \mathcal{M}''$, the channel i^* that provides the minimum needed transmit power for the transmitting drone can be found as:

$$i^* = \arg\min_{i \in \mathcal{M}''} \left\{ P_R^{(i)} \right\} \tag{10}$$

Algorithm 1 and Figure 2 provide the pseudo-code and the block diagram of the proposed power allocation and channel assignment protocol (APCA).

Proposition 1: Our proposed optimal power allocation algorithm is applicable to any arbitrary channel matrix H with $r < N$ (i.e., r parallel channels instead of N).

Proof: It has been shown that an $N \times N$ MIMO channel with arbitrary H matrix of rank $r < N$ can be represented by r orthogonal channels with gain λ_i, $i = \{1, \ldots r\}$, where λ_i is the ith Eigenvalue of HH^H. In this case, the power should be allocated over the r Eigen channels instead of the N physical channels [32]. Hence, our proposed algorithm can be executed over the r Eigen channels, resulting in a total achieved rate of $\sum_{j=1}^{r} R_j^{(i)}$ over each idle channel i.

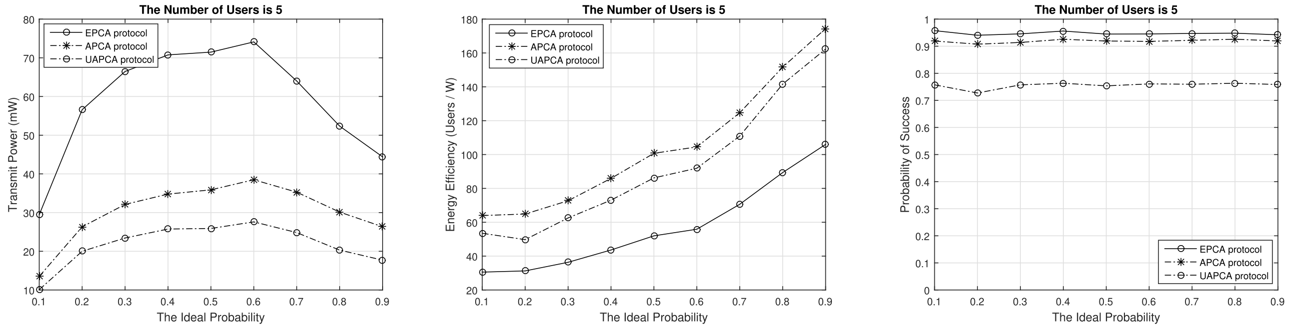
V. PERFORMANCE EVALUATION

We conduct simulation experiments using Matlab programs to evaluate the performance of our adaptive power-minimization channel assignment (APCA) protocol and compare its performance with that or reference protocols [42]. The CVX solver has been used to solve the convex optimization problems and generate the reported results [43].

A. SIMULATION SETUP

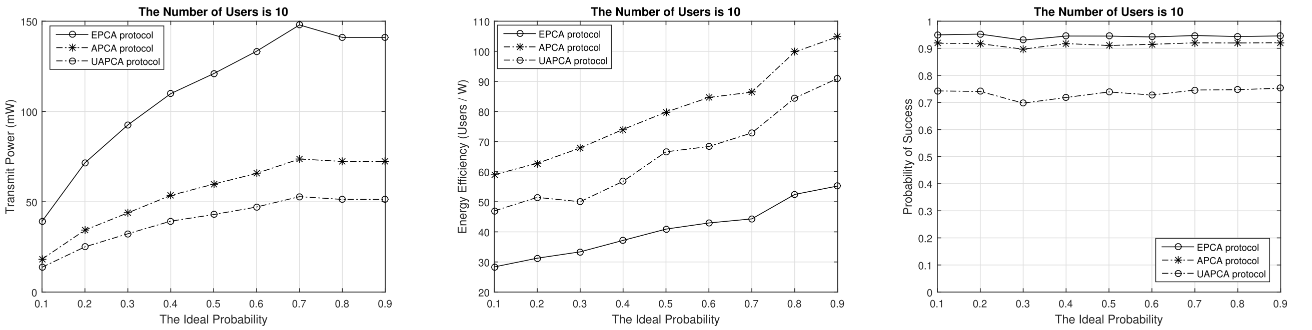
We consider a network of drones in an indoor environment that coexists with a PU network with 8 channels. These drones are served by a CR BS. We assume that the number of drones is 8. The drones opportunistically utilize the 8 PU channels, where the bandwidth of each channel is set to 5 MHz. The data packet size and the noise spectral density are set to $D = 2$ KB and 10^{-17} W/Hz, respectively. Furthermore, the average availability periods of the PU channels are given by $\mu = \xi \times [0.02, 0.02, 0.025, 0.025, 0.04, 0.04, 0.05, 0.05]$, where ξ represents the availability-time factor. The required probability of success is assumed to be $\gamma = 0.9$, unless stated otherwise. We set the operating frequency for the uplink indoor channel model to $f = 900$ MHz, $b = 0.01$, $f_0 = 39.5$ GHz, and the path loss exponent to $n = 2.59$. Each drone is equipped with four antennas, i.e., $N = 4$. We set the maximum transmitted power per antenna to 500 mW and the maximum total transmit power for each drone to 1 W. In our simulation experiments, we compare the performance of the proposed APCA protocol with that of two reference protocols: the equal-power channel assignment protocol (EPCA) and the adaptive power-minimization CR-unaware channel assignment (UAPCA) protocol under different PU activity levels [42], [44]. The APCA and EPCA protocols are designed while being aware of the dynamic PU activity, whereas the UAPCA does not account for the PU activity. On then other hand, EPCA assigns power equally among the different antennas, whereas APCA and UAPCA perform per-antenna power control. Furthermore, we investigate the effect of idle probability P_I, probability of success requirement γ, PU average channel availability duration, demand rate, and the number of drones on network performance. Our main performance metrics are the required transmit power, energy efficiency, achieved success probability, and user satisfaction. Energy efficiency is defined as the ratio between the number of successfully served drones to the total consumed transmit power (Users/Watt). On the other hand, user

$$\mathbf{H}_f(P_j^{(i)}) = \begin{bmatrix} \frac{-W{\alpha_1^{(i)}}^2}{(1+\alpha_1^{(i)}P_1^{(i)})^2} & 0 & \cdots & 0 & 0 \\ 0 & \frac{-W{\alpha_2^{(i)}}^2}{(1+\alpha_2^{(i)}P_2^{(i)})^2} & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & \frac{-W{\alpha_{N-1}^{(i)}}^2}{(1+\alpha_{N-1}^{(i)}P_{N-1}^{(i)})^2} & 0 \\ 0 & 0 & \cdots & 0 & \frac{-W{\alpha_N^{(i)}}^2}{(1+\alpha_N^{(i)}P_N^{(i)})^2} \end{bmatrix} \tag{8}$$



(a) Transmit power with $K = 5$. (b) Energy efficiency $K = 5$. (c) Probability of success $K = 5$.

FIGURE 3. **System performance versus idle probability for $M = 8$.**



(a) Transmit power $K = 10$. (b) Energy efficiency $K = 10$. (c) Probability of success $K = 10$

FIGURE 4. **System performance versus idle probability for $M = 8$.**

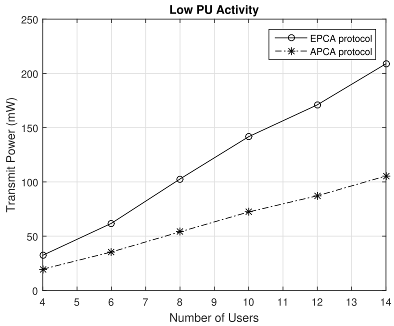
TABLE 1. **User satisfaction with high, moderate and low PU activity for different number of CR-capable drones.**

Activity	$P_I = 0.1$		$P_I = 0.5$		$P_I = 0.9$	
Drones	APCA	EPCA	APCA	EPCA	APCA	EPCA
4	1.55	1.61	3.17	3.26	3.67	3.77
6	1.78	1.85	3.88	4.01	5.48	3.63
8	1.93	1.98	4.23	4.37	6.73	6.94
10	1.98	2.08	4.91	5.06	7.58	7.8
12	2.27	2.35	5.44	5.60	8.41	8.66
14	2.44	2.52	5.81	5.99	9.22	9.49

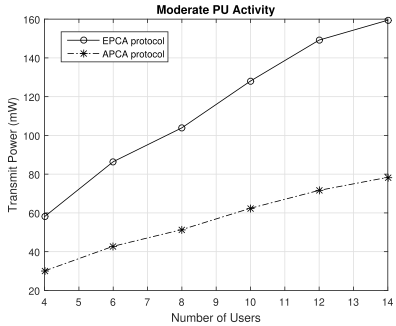
satisfaction is defined as the average number of successfully served drones with their required QoS requirements.

B. SIMULATION RESULTS

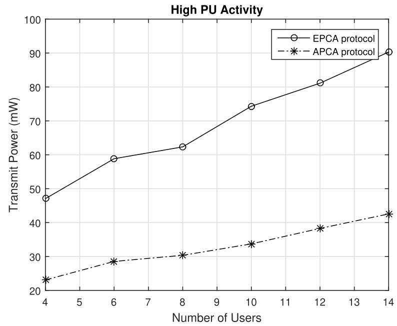
We first investigate the system performance of the APCA, EPCA, and UAPCA protocols as a function of the PU idle probability (P_I). Fig. 3 and Fig. 4 demonstrate the overall transmit power, energy efficiency, and achieved success probability performance as a function of P_I for 5 and 10 CR-equipped drones, respectively. As it is seen in Figs. 3 and 4, for a given QoS requirement and the same number of PU channels, our proposed APCA protocol significantly outperforms the other two protocols in terms of energy efficiency and consumed power, irrespective of P_I. In addition, the APCA and EPCA protocols always provide the required QoS guarantees because of their inherent PU activity awareness, whereas the UAPCA cannot provide the required success probability requirements. Specifically, Fig. 3a shows that the total transmit power increases as P_I increases up to $P_I = 0.5$ for all protocols. Then, the required transmit power decreases as P_I increases beyond 0.5. This is because for $P_I \leq 0.5$, higher P_I values increase the availability of ideal channels, but still the number of ideal channels is less than the number of competing drones. Thus, increasing P_I up to 0.5 increases the number of served drones, resulting in a higher total required transmitted power. However, for $P_I \geq 0.5$, the number of available channels becomes greater than the number of competing drones (i.e., 5). In this case, all competing drones will be served as long as $P_I \geq 0.5$, but increasing P_I results in a greater number of idle channels allowing the drones to select the most power-efficient channels, resulting in reduced total transmit power as demonstrated in Fig. 3a. On the other hand, Fig. 3b reveals that the energy efficiency increases as P_I increases. This is expected as increasing P_I results in more idle channels, and hence higher number of served drones. A higher number of served drones results in higher energy efficiency. For a network of 5 drones, Fig. 3c reveals that the probability of success requirement γ is always guaranteed for the APCA and EPCA protocols, irrespective of P_I. However, the UAPCA protocol does not provide the required QoS requirements. This is because the APCA and EPCA protocols are PU activity-aware, whereas UAPCA



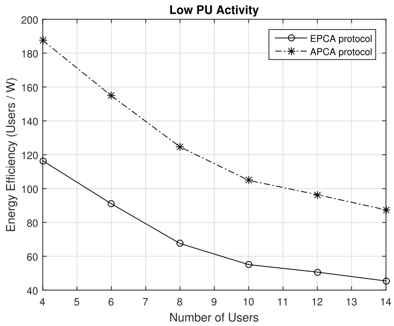
(a) Transmit power, $P_I = 0.1$



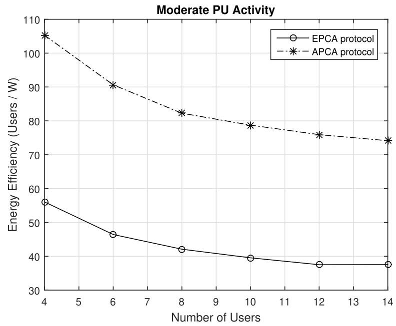
(b) Transmit power, $P_I = 0.5$



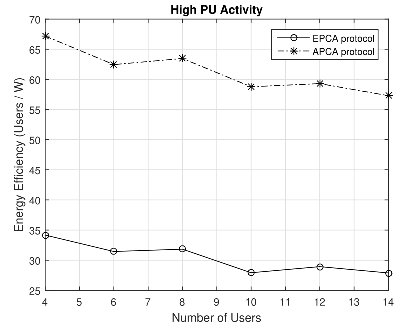
(c) Transmit power, $P_I = 0.9$



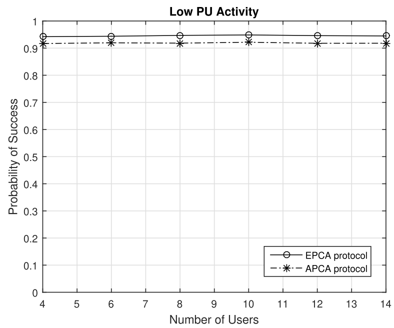
(d) Energy efficiency, $P_I = 0.1$



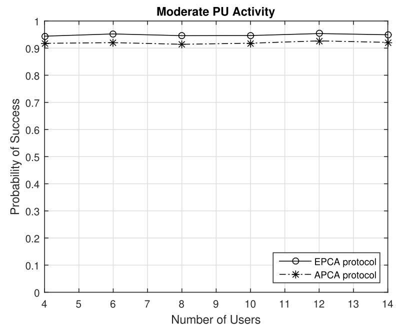
(e) Energy efficiency, $P_I = 0.5$



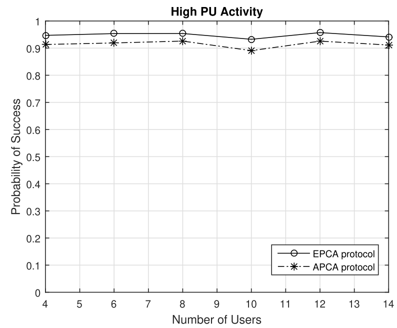
(f) Energy efficiency, $P_I = 0.9$



(g) Probability of success, $P_I = 0.1$



(h) Probability of success, $P_I = 0.5$



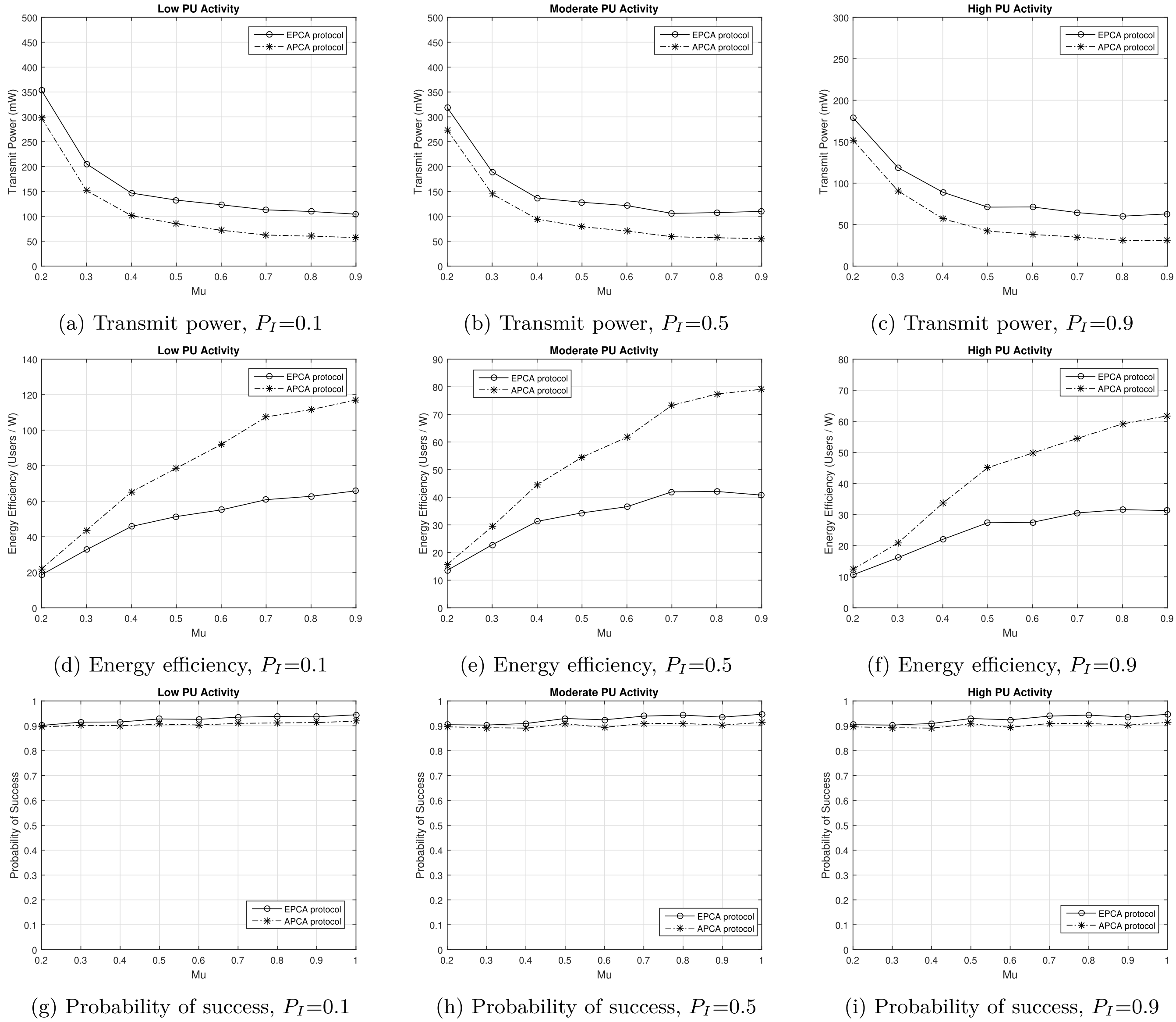
(i) Probability of success, $P_I = 0.9$

FIGURE 5. System performance versus the number of CR users.

does not account for the impact of PU activity on system performance.

Furthermore, For a network of 10 CR-based drones, Fig. 4 shows the overall transmit power, energy efficiency, and achieved success probability performance as a function of P_I for the three protocols. Fig. 4a indicates that the transmit power increases as P_I increases. This is because higher values of P_I result in more channel availability, leading to an increase in the number of served users and the total needed transmitted power. Fig. 4b reveals that the increase in the number of served drones, as a result of increasing P_I, enhances the energy efficiency performance despite the need for a higher total transmitted power. For the case of 10 contending drones, Fig. 4c reveals that the probability of success requirement γ is always guaranteed, irrespective of P_I. Because the UAPCA protocol does not provide the required probability of success requirements, in the rest of our experimental results, we focus on investigating the performance of the APCA and EPCA protocols.

Fig. 5 shows the overall transmit power, energy efficiency, and achieved success probability performance under high, moderate, and low PU activity levels for a different number of CR-based drones for both the APCA and EPCA protocols. This figure reveals that, for a given QoS requirement and the same number of served drones, our proposed APCA protocol significantly outperforms the reference protocol in terms of energy efficiency and consumed power, irrespective of P_I and number of served users. Specifically, Fig. 5a, 5b and 5c indicate that the transmit power increases as the number of CR-based drones increases as serving a larger number of drones results in a higher total transmitted power. Figs. 5d, 5e and 5f indicate that the energy efficiency decreases as the number of served CR-based drones increases, irrespective of P_I. This is because serving a larger



(a) Transmit power, P_I=0.1 (b) Transmit power, P_I=0.5 (c) Transmit power, P_I=0.9

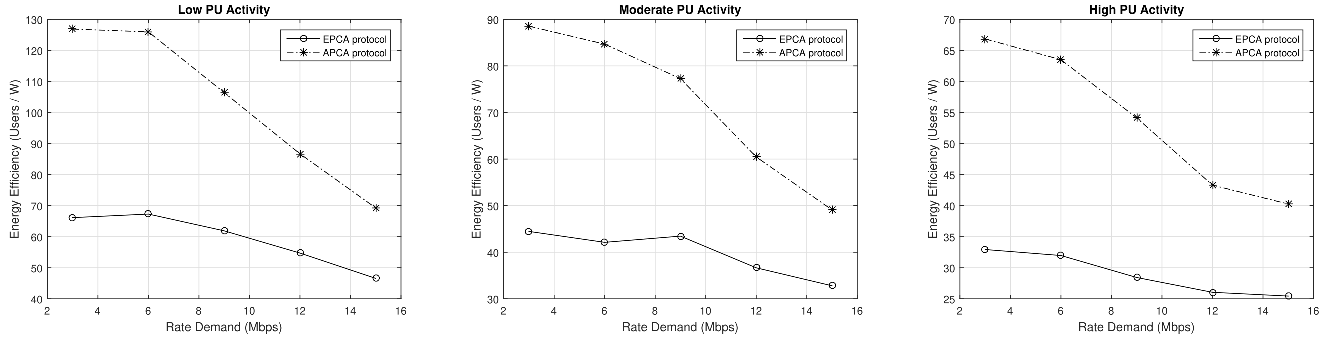
(d) Energy efficiency, P_I=0.1 (e) Energy efficiency, P_I=0.5 (f) Energy efficiency, P_I=0.9

(g) Probability of success, P_I=0.1 (h) Probability of success, P_I=0.5 (i) Probability of success, P_I=0.9

FIGURE 6. **System performance versus the PU average channel availability duration.**

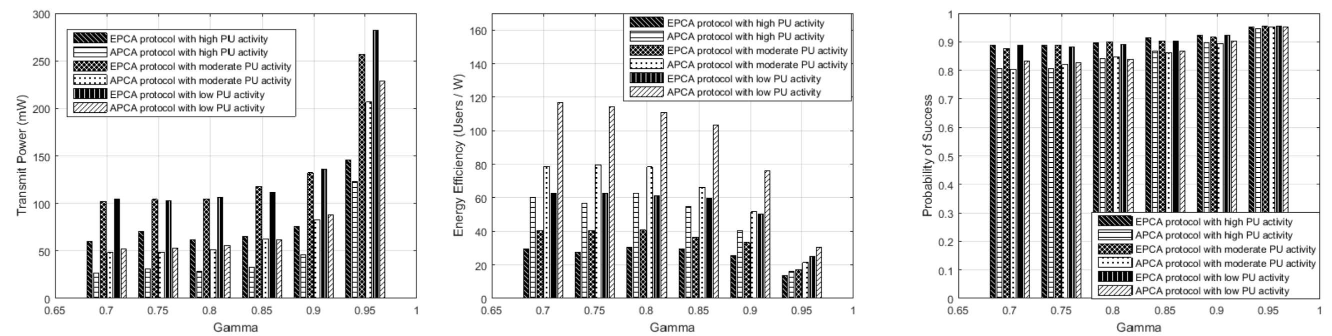
number of drones using the same number of PU channels requires higher total transmitted power, which negatively impacts energy efficiency. Figs. 5g, 5h and 5i demonstrate that the probability of success requirement γ is always guaranteed for both protocols, irrespective of number of drones and P_I. Table 1 shows the user satisfaction under different PU activity levels for a varying number of CR drones for the APCA and EPCA protocols. This table indicates that both protocols provide comparable levels of user satisfaction. This table also indicates that user satisfaction increases as the number of drones increases (i.e., the number of served drones that opportunistically utilize the available PU channels increases).

Furthermore, Fig. 6 shows the overall transmit power, energy efficiency, and achieved success probability performance under high, moderate, and low PU activity levels for different values of the average availability periods of the PU channels (μ). This figure reveals that, for a given QoS requirement and the same number of served drones, our proposed APCA protocol significantly outperforms the reference protocol in terms of energy efficiency and consumed power, irrespective of μ and P_I. Specifically, Figs. 6a, 6b and 6c indicate that the transmit power decreases as μ increases. This is because higher values of μ result in a longer PU channel availability time, leading to higher success probability and reduced power consumption. Figs. 6d, 6e and 6f indicate that the energy efficiency increases as μ increases. This is because increasing μ increases the success probability, resulting in less transmit power requirement and a larger number of served drones. Under various PU activity



(a) Energy efficiency, $P_I = 0.1$ (b) Energy efficiency, $P_I = 0.5$ (c) Energy efficiency, $P_I = 0.9$

FIGURE 7. System performance versus the required rate demand.



(a) Transmit power (b) Energy efficiency (c) Probability of success

FIGURE 8. System performance versus γ with $\xi = 0.4746$.

TABLE 2. User satisfaction with high, moderate and low PU activity for different μ.

Activity	P_I=0.1		P_I=0.5		P_I=0.9	
μ	APCA	EPCA	APCA	EPCA	APCA	EPCA
0.1	1.82	1.81	4.13	4.11	6.4	6.36
0.2	1.88	1.9	4.3	4.32	6.53	6.57
0.3	1.89	1.92	4.26	4.32	6.62	6.72
0.4	1.92	1.96	4.20	4.28	6.61	6.72
0.5	1.9	1.95	4.31	4.41	6.66	6.81
0.6	1.9	1,96	4.35	4.45	6.62	6.79
0.7	1.91	1.97	4.32	4.45	6.7	6.88
0.8	1.83	1.9	4.40	4.52	6.69	6.88
0.9	1.9	1.97	4.34	4.48	6.7	6.87
1	1.94	2.01	4.40	4.54	6.76	6.95

levels, Figs. 6g, 6h and 6i show that the probability of success requirement γ is always guaranteed, regardless of μ. This is because our proposed protocol adapts its operating parameters to achieve the imposed QoS requirements. Table 2 shows the user satisfaction under high, moderate, and low PU activity levels for different values of μ. This table indicates that user satisfaction increases as μ increases. This is because increasing μ results in higher availability time for the assigned channels, which significantly reduces the number of drooped CR-enabled drone transmissions. Table 2 reveals that APCA and EPCA protocols show comparable performance in terms of user satisfaction.

Fig. 7 shows the energy efficiency performance under high, moderate, and low PU activity levels versus the required rate demand for the APCA and EPCA protocols. This figure reveals that, for a given QoS requirement and the same number of served drones, our proposed APCA protocol significantly outperforms the reference protocol in terms of energy efficiency and consumed power for all values of rate demand and P_I. Specifically, Figures 7a, 7b and 7c indicate that the energy efficiency decreases as the required rate demand increases. This is because, with a fixed number of CR drones, a fixed number of PU channels, and a given success requirement γ, achieving higher rate demands requires higher total transmit power, leading to a significant reduction in energy efficiency performance. Other results not shown here reveal that the probability of success requirement γ is always guaranteed, irrespective of the rate demand and the PU activity levels.

Fig. 8 reports the overall transmit power, energy efficiency, and achieved success probability performance under high, moderate, and low PU activity levels as a function of γ for the APCA and EPCA protocols. This figure reveals that our proposed protocol significantly outperforms the EPCA protocol in terms of the consumed power and energy efficiency for the same number of served users and PU channels under different values of γ. The impact of increasing γ appears when γ exceeds the value of 0.7. This is because

TABLE 3. User satisfaction with high, moderate and low PU activity for different rate demand.

Activity	P_I=0.1		P_I=0.5		P_I=0.9	
R_D	APCA	EPCA	APCA	EPCA	APCA	EPCA
3	1.794	1.893	4.316	4.536	6.605	6,906
6	1.951	2.028	4.313	4.455	6.775	6.975
9	2.117	2.169	4.468	4.555	6.906	7.02
12	1.988	2.007	4.461	4.496	6.973	7.027
15	2.038	2.05	4.655	4.68	7.108	7.128

achieving $\gamma \geq 0.7$ requires achieving a higher data rate than the required rate demand. Fig. 8a indicates that the transmit power increases as γ increases. By increasing γ, higher transmission rates are needed to fulfill the success probability requirements. In order to achieve the required higher data rates, higher transmit power levels are needed. According to Fig. 8b, as γ increases, energy efficiency decreases. This is because achieving higher values of γ requires increasing the transmit power. Fig. 8c reveals that the probability of success requirement is always guaranteed for all values of γ.

Table 3 shows the user satisfaction under high, moderate, and low PU activity levels for different values of the required rate demand. This table indicates that the APCA and EPCA protocols depict comparable user satisfaction performance. Note that the change in the demand rate does not affect the level of user satisfaction. This is because both protocols adapt their power allocation policy based on the required rate demand.

VI. CONCLUSION

This paper integrated the CR and MIMO technologies into an indoor flying network for the purpose of enhancing the overall power consumption and energy efficiency. Specifically, we proposed an adaptive power-allocation and channel assignment, i.e., APCA, protocol that aims to minimize the per-drone transmit power while achieving rate demand, total power, probability of success, and per-antenna constraints. The proposed APCA protocol consists of two phases power allocation and channel assignment. In the first phase, the optimal power allocation per antenna over each ideal channel for the communicating drone is computed through solving convex power-minimization problems, each with the objective of minimizing the overall transmission power over each idle channel. Given the computed optimal power allocation, in the second phase, APCA assigns the channel with the minimum needed transmit power to the drone transmission. The advantage of our proposed protocol is that it determines the most energy-efficient channel that requires the least possible transmit power. We compared the performance of the proposed protocol with that of the equal-power protocol. Simulation results revealed that our proposed APCA protocol enhances the performance in terms of the overall total transmitted power and energy efficiency.

REFERENCES

[1] A. M. Johnson, C. J. Cunningham, E. Arnold, W. D. Rosamond, and J. K. Zègre-Hemsey, "Impact of using drones in emergency medicine: What does the future hold?" *Open Access Emergency Med.*, vol. 13, p. 487, Nov. 2021.

[2] O. Bai and H. Chu, "Drones in education: A critical review," *Turkish J. Comput. Math. Educ.*, vol. 12, no. 11, pp. 1722–1727, 2021.

[3] L.-S. Yoo, J.-H. Lee, Y.-K. Lee, S.-K. Jung, and Y. Choi, "Application of a drone magnetometer system to military mine detection in the demilitarized zone," *Sensors*, vol. 21, no. 9, p. 3175, May 2021.

[4] Y. Li, H. Zhang, H. Ji, and X. Li, "UAV-assisted cellular communication: Joint trajectory and coverage optimization," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Mar. 2021, pp. 1–6.

[5] S. Tripathi, O. J. Pandey, and R. M. Hegde, "Optimal data transfer in UAV-assisted edge-networks using 3D beamforming," in *Proc. Nat. Conf. Commun. (NCC)*, Jul. 2021, pp. 1–6.

[6] E. A. Kadir, R. Shubair, S. K. A. Rahim, M. Himdi, M. R. Kamarudin, and S. L. Rosa, "B5G and 6G: Next generation wireless communications technologies, demand and challenges," in *Proc. Int. Congr. Adv. Technol. Eng. (ICOTEN)*, Jul. 2021, pp. 1–6.

[7] H. Albinsaid, K. Singh, A. Bansal, S. Biswas, C.-P. Li, and Z. J. Haas, "Multiple antenna selection and successive signal detection for SM-based IRS-aided communication," *IEEE Signal Process. Lett.*, vol. 28, pp. 813–817, 2021.

[8] A. Nasser, H. A. H. Hassan, J. A. Chaaya, A. Mansour, and K.-C. Yao, "Spectrum sensing for cognitive radio: Recent advances and future challenge," *Sensors*, vol. 21, no. 7, p. 2408, Mar. 2021.

[9] A. Akbar, S. Jangsher, and F. A. Bhatti, "NOMA and 5G emerging technologies: A survey on issues and solution techniques," *Comput. Netw.*, vol. 190, May 2021, Art. no. 107950.

[10] A. Ahmed, Z. Elsaraf, F. A. Khan, and Q. Z. Ahmed, "Cooperative non-orthogonal multiple access for beyond 5G networks," *IEEE Open J. Commun. Soc.*, vol. 2, pp. 990–999, 2021.

[11] K. K. Vaigandla and N. Venu, "Survey on massive MIMO: Technology, challenges, opportunities and benefits," *YMER Digit.*, vol. 20, no. 11, pp. 271–282, Nov. 2021.

[12] D. Borges, P. Montezuma, R. Dinis, and M. Beko, "Massive MIMO techniques for 5G and beyond—Opportunities and challenges," *Electronics*, vol. 10, no. 14, p. 1667, Jul. 2021.

[13] T. M. Inbamalar, "A study of cognitive radio sensing techniques for optimum spectrum utilization," *Recent Adv. Comput. Sci. Commun.*, vol. 15, no. 3, pp. 354–366, Mar. 2022.

[14] V. S. Ramaiah, B. Singh, A. R. Raju, G. N. Reddy, K. Saikumar, and D. Ratnayake, "Teaching and learning based 5G cognitive radio application for future application," in *Proc. Int. Conf. Comput. Intell. Knowl. Economy (ICCIKE)*, Mar. 2021, pp. 31–36.

[15] X. Luo, L. You, J. Lv, and C. Zhong, "Multidomain narrowband interference intelligent suppression method based on cognitive radio and MIMO in UAV data link," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–14, May 2022.

[16] H. Mathur and T. Deepa, "A survey on advanced multiple access techniques for 5G and beyond wireless communications," *Wireless Pers. Commun.*, vol. 118, no. 2, pp. 1775–1792, May 2021.

[17] J. R. Bhat and S. A. Alqahtani, "6G ecosystem: Current status and future perspective," *IEEE Access*, vol. 9, pp. 43134–43167, 2021.

[18] C. Maraveas, D. Piromalis, K. Arvanitis, T. Bartzanas, and D. Loukatos, "Applications of IoT for optimized greenhouse environment and resources management," *Comput. Electron. Agricult.*, vol. 198, Jul. 2022, Art. no. 106993.

[19] S. V. Lakshmi, J. Janet, P. Kavitha Rani, K. Sujatha, K. Satyamoorthy, and S. Marichamy, "Role and applications of IoT in materials and manufacturing industries—Review," *Mater. Today, Proc.*, vol. 45, pp. 2925–2928, Jan. 2021.

[20] C. K. Sheemar and D. Slock, "Beamforming for bidirectional MIMO full duplex under the joint sum power and per antenna power constraints," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Jun. 2021, pp. 4800–4804.

[21] Z. Wang and L. Vandendorpe, "Power allocation for energy efficient multiple antenna systems with joint total and per-antenna power constraints," *IEEE Trans. Commun.*, vol. 66, no. 10, pp. 4521–4535, Oct. 2018.

[22] H. Hu, Y. Huang, X. Da, H. Zhang, L. Ni, and Y. Pan, "Optimization of energy management for UAV-enabled cognitive radio," *IEEE Wireless Commun. Lett.*, vol. 9, no. 9, pp. 1505–1508, Sep. 2020.

[23] Y. Zhou, F. Zhou, H. Zhou, D. W. K. Ng, and R. Q. Hu, "Robust trajectory and transmit power optimization for secure UAV-enabled cognitive radio networks," *IEEE Trans. Commun.*, vol. 68, no. 7, pp. 4022–4034, Mar. 2020.

[24] D. Deng and M. Zhu, "Joint UAV trajectory and power allocation optimization for NOMA in cognitive radio network," *Phys. Commun.*, vol. 46, Jan. 2021, Art. no. 101328.

[25] L. Zhu, J. Zhang, Z. Xiao, and R. Schober, "Optimization of multi-UAV-BS aided millimeter-wave massive MIMO networks," in *Proc. IEEE Global Commun. Conf.*, Dec. 2020, pp. 1–6.
[26] H. Ren, L. Li, W. Xu, W. Chen, and Z. Han, "Machine learning-based hybrid precoding with robust error for UAV mmWave massive MIMO," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2019, pp. 1–6.
[27] W. Tan, S. Li, C. He, W. Tan, X. Gu, and Z. Shi, "Achievable rate of UAV-based communication with uniform circular arrays in Ricean fading," *Phys. Commun.*, vol. 32, pp. 185–191, Feb. 2019.
[28] S. Grant, J.-F. Cheng, L. Krasny, K. Molnar, and Y. P. E. Wang, "Per-antenna-rate-control (PARC) in frequency selective fading with SIC-GRAKE receiver," in *Proc. IEEE 60th Vehicular Technol. Conf.*, vol. 2, Sep. 2004, pp. 1458–1462.
[29] A. A. Khuwaja, Y. Chen, N. Zhao, M.-S. Alouini, and P. Dobbins, "A survey of channel modeling for UAV communications," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 4, pp. 2804–2821, 4th Quart., 2018.
[30] K. Haneda et al., "Indoor 5G 3GPP-like channel models for office and shopping mall environments," in *Proc. IEEE Int. Conf. Commun. Workshops (ICC)*, May 2016, pp. 694–699.
[31] O. J. Pandey and R. M. Hegde, "Node localization over small world WSNs using constrained average path length reduction," *Ad Hoc Netw.*, vol. 67, pp. 87–102, Dec. 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1570870517301828
[32] F. Bohagen, P. Orten, and G. E. Oien, "Design of optimal high-rank line-of-sight MIMO channels," *IEEE Trans. Wireless Commun.*, vol. 6, no. 4, pp. 1420–1425, Apr. 2007.
[33] A. A. Hutter, F. Platbrood, and J. Ayadi, "Analysis of MIMO capacity gains for indoor propagation channels with LOS component," in *Proc. 13th IEEE Int. Symp. Pers., Indoor Mobile Radio Commun.*, vol. 3, Sep. 2002, pp. 1337–1341.
[34] P. F. Driessen and G. J. Foschini, "On the capacity formula for multiple input-multiple output wireless channels: A geometric interpretation," *IEEE Trans. Commun.*, vol. 47, no. 2, pp. 173–176, Feb. 1999.
[35] T. Haustein and U. Kruger, "Smart geometrical antenna design exploiting the LOS component to enhance a MIMO system based on Rayleigh-fading in indoor scenarios," in *Proc. 14th IEEE Proc. Pers., Indoor Mobile Radio Commun.*, vol. 2, Sep. 2003, pp. 1144–1148.
[36] K. Sakaguchi, "MIMO channel capacity in an indoor line-of-sight (LOS) environment," *IEICE Trans. Commun.*, vol. 88, no. 7, pp. 3010–3019, Jul. 2005.
[37] M. T. Ivrlac, W. Utschick, and J. A. Nossek, "Fading correlations in wireless MIMO communication systems," *IEEE J. Sel. Areas Commun.*, vol. 21, no. 5, pp. 819–828, Jun. 2003.
[38] K. Honda, "Over-the-air testing of a massive MIMO antenna with a full-rank channel matrix," *Sensors*, vol. 22, no. 3, p. 1240, Feb. 2022. [Online]. Available: https://www.mdpi.com/1424-8220/22/3/1240
[39] S. Kamal and B. Nazar, "Performance evaluation of combining SMT-ETX metric with POS scheme for implementing multilayer multicast mobile ad hoc network (MANET) CRN," *IET Commun.*, vol. 14, no. 4, pp. 610–618, Mar. 2020.
[40] F. E. Matyjas, *Spectrum Sharing in Wireless Networks: Fairness, Efficiency, and Security*. Boca Raton, FL, USA: CRC Press, 2016.
[41] H. Wang, C. Liu, Z. Shi, Y. Fu, and R. Song, "On power minimization for IRS-aided downlink NOMA systems," *IEEE Wireless Commun. Lett.*, vol. 9, no. 11, pp. 1808–1811, Nov. 2020.
[42] H. W. Lee and S. Chong, "Downlink resource allocation in multi-carrier systems: Frequency-selective vs. equal power allocation," *IEEE Trans. Wireless Commun.*, vol. 7, no. 10, pp. 3738–3747, Oct. 2008.
[43] M. Grant and S. Boyd, "CVX: MATLAB software for disciplined convex programming, version 2.1," Stanford Univ., San Francisco, CA, USA, Tech. Rep. TR1, 2014. [Online]. Available: https://cvxr.com/cvx
[44] D. Mishra and G. C. Alexandropoulos, "Jointly optimal spatial channel assignment and power allocation for MIMO SWIPT systems," *IEEE Wireless Commun. Lett.*, vol. 7, no. 2, pp. 214–217, Apr. 2018.

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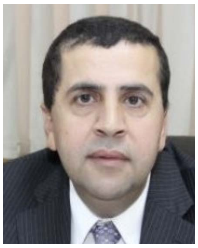

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