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Analysis of some Cooperative Methods for Wireless Communications

Ph.D. dissertation summary

by

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Budapest, Hungary
2025

1 Introduction

Unmanned aerial vehicles (UAVs), also known as drones, are significantly transforming mobile communications by providing greater flexibility and efficiency. Acting as relay nodes or aerial base stations, UAVs can expand network coverage to remote and under the served areas and increase capacity during peak demand events. Operating from above, drones can bypass obstructions that hinder terrestrial signals, ensuring reliable connectivity where traditional infrastructure may fall short or not available at all. Their ability to move allows them to adjust in real-time to evolving network conditions, optimizing resource use and reducing interference. As we progress into the 5G era and beyond, integrating UAVs into mobile networks is set to transform connectivity, strengthening its reliability and expanding its reach, thereby bridging gaps in the digital landscape [1].

As UAV-assisted become more integral across various sectors, optimizing their trajectory and thus the carried gNB communication capabilities is crucial [2], [3]. A major challenge in UAV communication systems is co-channel interference (CCI), which can greatly affect wireless links' reliability and performance. Addressing CCI, where multiple UAVs or ground stations on the same frequency interfere with each other, is essential for maintaining robust communication links in congested environments. Advanced communication techniques like dual-hop and cooperative diversity can potentially improve UAV communication networks [4] and [5]. Dual-hop communication allows drones to act as relay nodes, bypassing direct interference sources and extending communication range, while cooperative diversity employs collaborative signal processing among UAVs to counteract CCI effects, forming virtual antenna arrays to enhance communication link resilience [6], [7] and [8].

Incorporating machine learning into UAV operations offers promising strategies for optimizing 5G and future networks. This research focuses on studying the CCI affect on the dual-hop relay network and to derive the required statistical formulas which are needed to investigate the network performance and efficiency in terms of bit-error probability and outage probability. Moreover, another main target is to investigate the performance and efficiency of the introduced cooperative diversity technique to the proposed dual-hop network. The investigation of the affect of CCI on the network performance and efficiency in term of outage and bit-error rate probabilities which are derived in this study. Additionally, this research aims to develop and evaluate machine learning procedures to enhance network performance by addressing the complexities and dynamics of modern wireless communication systems. Using deep reinforcement learning (DRL), the study aims to optimize both the trajectory of UAVs and the resources they managed by the carried gNB. By incorporating ground user mobility into the DRL model, the research seeks to solve optimization challenges and achieve optimal solutions, ultimately improving the quality of service and user experience in 5G networks. This intersection of machine learning and UAV technology represents a significant advancement in the field, promising to further elevate the capabilities and effectiveness of mobile communication systems.

2 Motivations and goals

Drones are changing the game for mobile communications, bringing flexibility and efficiency like never before. Think of them as flying cell towers, unmanned aircraft can act as temporary relays or even full-fledged base stations in the sky. They're especially powerful in hard-to-reach areas, filling gaps where traditional towers can't, or boosting capacity during big events when networks get overloaded. Because they fly above the ground, drones avoid obstacles that usually block signals, delivering stronger, more reliable connections. What's really cool? They can move on the fly (literally!), adjusting their position to improve coverage, reduce interference, and make the best use of network resources. As we step into the 5G era and beyond, drones are set to revolutionize connectivity—making it stronger, more adaptable, and far-reaching. They're not just improving networks; they're helping bring the digital world to places it's never been before.

As UAVs continue to play an increasingly integral role in various domains, the optimization of their communication capabilities becomes paramount. Thus my studies objectives were listed as the following:

- Investigating the integration of dual-hop communication within UAV networks in the context of CCI interference presents an opportunity to assess the potential improvements in link reliability and network coverage. Where we derive the statistical formulas required to analysis the network performance in terms of bit error rate and outage probability. We assume all links are subjected to α-μ fading channel.

- Explore the intersection of dual-hop communication, cooperative diversity, and CCI interference mitigation within UAV communication networks. By investigating the effect of CCI on the communication channel, we derived the necessary statistical equations such as the probability density functions and cumulative density functions which are used to build and derive the performance metrics for the network performance such as bit error rate and outage probability, where the fading model is the α-μ fading channel.

- Deploy deep reinforcement learning framework, to optimize the operation of 5G and beyond networks, taking advantage of the UAV carrying a gNB to provide mobile services. The proposed procedures will enhance network performance, reliability, efficiency, and security, optimally improving the quality of service and user experience in 5G deployments where we deployed an RL framework to jointly optimize the trajectory of the UAV and the resources allocated by the carried by the UAV. In this approach, we considered the mobility of the ground user while designing the DRL model in order to solve the optimization problem and reach the optimal solution.

3 Methodology

Digital communication which refers to the process of transferring information using digital signals over a communication channel. Which is fundamental in modern technologies, enabling efficient and reliable transmission of information across various media, including wireless and in this thesis we focus on dual-hop cooperative systems. Dual-hop cooperative systems are evaluated based on performance metrics such as Bit Error Rate (BER), Signal-to-Noise Ratio (SNR), and the outage probability (P_{out}).

The first step involves developing a detailed system model of the dual-hop cooperative network. This includes defining the nodes of the network, which means to identify the source, relay, and destination nodes. The relay node assists in forwarding the signal from the source to the destination and deploying a forwarding algorithm such as amplify-and-forward (AF) or decode-and-forward (DF). The other part is to model the wireless channel Characteristics among the network nodes, and this can be done using probabilistic tools. This includes characterizing the fading and noise processes, typically assuming Rayleigh or Rician fading models as in [9] and [10], or assuming α-μ fading channel [11]. The second stage of the approach is probability analysis, which involves utilizing the probabilistic models to evaluate the behavior of the channels and the impact of noise and interference. In this stage, two steps are to be used: define the signal and noise as random variables with specific Probability Density Functions (PDFs) and Cumulative Distribution Functions (CDFs). Then use Moment-Generating Functions (MGFs) to derive key statistical properties and simplify the calculation of performance metrics such as Bit Error Rate (BER), Signal-to-Noise Ratio (SNR), and outage probability (P_{out}) [12].

Comparative analysis can be performed to analyze different relay strategies and adding cooperative diversity to the dual-hop network and analyze the performance for this enhancement and compare it to the dual-hop network, another comparative analysis is to compare different channel conditions such as Rayleigh or Nakagami-m fading models to the α-μ fading model.

Reinforcement learning (RL) is a promising approach that can be used to optimize network resources. Where RL is considered an efficient method to manage complex and dynamic network environments. This involves using RL to make real-time decisions about resource allocation, traffic management, and network configuration to improve performance metrics such as throughput, latency, and energy efficiency. In order to apply RL to solve the problem, we designed our system as a Markov decision problem (MDP). MDP consists of tuple of five elements $\langle S, A, p, r, \gamma \rangle$, where S represents the system state set, A action space set, $p : S \times A \times S \in [0, 1]$ and represents the Transition Probability Matrix between the states, $r : S \times A \times S \rightarrow \mathbb{R}$ denotes the immediate reward between state transitions; finally $\gamma \in [0, 1]$ which represent the discount factor [13]. Different RL algorithms can be deployed to optimize the network resources and the UAV trajectory, specially deep reinforcement learning (DRL) which is suitable for discrete state space, another RL algorithm that can be deployed is the policy gradient method which is known as Proximal Policy Optimization (PPO) [14].

4 Theses

4.1 Impact of Co-Channel Interference on Performance of Cooperative Wireless Ad-hoc Networks over $\alpha - \mu$ fading channels

Unmanned Aerial Vehicles can act as a R in dual-hop networks shown in figure 4.1, where a source node S communicates with D through the relay node R. Let's assume that the destination and relay nodes were subjected to Co-Channel interfering signals from N-number and L-number Co-Channel Interferer $\{x_i\}_{i=1}^{N}$ and $\{x_k\}_{k=1}^{L}$ each with energy of E_i and E_k respectively. Another assumption is considering the amplify-and-forward (AF) relaying technique and the fading coefficients for all the links are assumed to be α-μ fading channel, the choice of fading channel type was based on its capacity to model small-scale fading and represent multipath fading channels in nonhomogeneous environments [11]. And can be used to generate additional fading channel models, such as Rayleigh, Nakagami-m, Chi, and one-sided Gaussian, where the α value equals 2.

The received signal at the destination node D after the amplification process of the transmitted signal from node S to the relay node R which is represented in [8, Eq.1], can be expressed as equation 4.1:

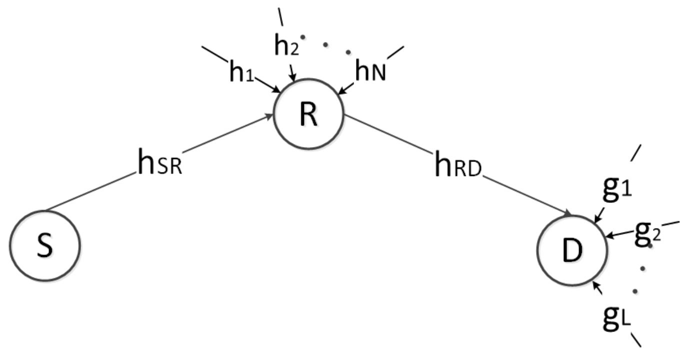

Figure 4.1: Dual-hop relay network with CCI at the relay and destination nodes.

$$y_{rd} = G_{AF}\sqrt{E_R}h_{rd}\Big[\sqrt{E_S}h_{sr}d_S + \sum_{i=1}^{N}\sqrt{E_i}h_i d_i\Big] + \sum_{k=1}^{L}\sqrt{E_k}g_k d_k + G_{AF}\sqrt{E_R}h_{rd}n_{sr} + n_{rd}. \tag{4.1}$$

where h_{SR} is the α-μ channel fading coefficient of the $S \to R$ link, E_S is the energy of the transmitted signal, d_S is the desired data with unit energy, h_i is the α-μ channel fading coefficient of the i-th interfere $\to R$ link, E_i is the energy of the i-th interferer at R and d_i is the i-th co-channel interferer's data with unit energy at the relay node. The additive-white-Gaussian-noise (AWGN) at the relay node is denoted as n_{SR} with a zero-mean N_o variance $\sim CN(0, N_o)$. On the other side, E_R represents the energy of the relay node transmitted signal, h_{RD} is the α-μ channel fading coefficient of the $R \to D$ link, E_k is the energy of the interference signal at the destination node, g_k is the α-μ fading coefficient of the interference channel at the destination, and d_k is the k^{th} co-channel interferer's data with unit energy at the destination, n_{SR} denotes the AWGN at the destination node with a zero-mean and N_o variance $\sim CN(0, N_o)$. The AF scaling gain G_{AF} is set to maintain the unit transmitted energy, the choice of this gain aims to invert the fading effect of the first hop to limit the output energy from the relay to be E_R. The gain factor has been applied at the relay such that,

$$G_{AF} = \sqrt{\frac{E_R}{E_S|h_{sr}|^2 + \sum_{i=1}^{N} E_i|h_i|^2 + N_o}}, \tag{4.2}$$

Thesis Group 1. I derived the exact expressions (the probability density function, the cumulative distribution function of the upper bound of the SINR, and the probability density function of N-number of I.I.D interferers using the moment generating function approach) that can be used to compute the error and outage performance of dual-hop amplify-and-forward relaying network over α-μ fading channels in the presence of co-channel interference's. I have shown that the new derived expressions cover the special cases with the specific values of α and μ considered in some previous works. For example the setting of ($\alpha = 2$, $\mu = 1$) and Nakagami-m ($\alpha = 2$, $\mu = m$ could be used to investigate the performance of the dual-hop amplify-and-forward relaying systems over other fading models such as Rayleigh and Nakagami-m, respectively. Published in [P1].

Thesis 1.1. I derived the CCI probability density function, which can be statistically modeled as the sum of N-number of independent but not identically distributed (I.N.D) α-μ variates $\left(\sum_{i=1}^{N}\gamma_{h_i}\right)$, where the PDF sum variates is expressed as:

$$f_{\sum_{i=1}^{N}\gamma_{h_i}}(\gamma_{h_I}) = \left(\frac{\mu_h}{\overline{\beta}_I}\right)^{N\mu_h}\frac{\gamma^{N\mu_h-1}}{\Gamma(N\mu_h)}e^{-\frac{\mu_h\gamma}{\overline{\beta}_I}}. \tag{4.3}$$

▪

Thesis 1.2. I derived the required statistical formulas for the dual-hop network, and built the effective signal-to-interference-and-noise ratio (SINR) statistical characteristics such as the PDF, CDF and MGF. The derived PDF for the upper bound which can be defined as $\{f_{\gamma_{up}}(\gamma) = f_{\gamma_{sr}^{eff}}(\gamma)\left[1 - F_{\gamma_{rd}^{eff}}(\gamma)\right] + f_{\gamma_{rd}^{eff}}(\gamma)\left[1 - F_{\gamma_{sr}^{eff}}(\gamma)\right]\}$, and is expressed as:

$$\begin{aligned}f_{\gamma_{up}}(\gamma) =& \frac{2}{\Gamma(\mu)^2}\left(\frac{\mu}{\overline{\beta}}\right)^{\mu}\left(\frac{\mu_I}{\overline{\beta}_i}\right)^{2M\mu_I}\sum_{j=0}^{\mu}\sum_{v=1}^{\mu}\sum_{n=0}^{v-1}\binom{\mu}{j}\binom{v-1}{n}(l\mu_I)_j(l\mu_I)_n \\ & \Gamma(\mu - v + 1)\left(\frac{\mu}{\overline{\beta}}\right)^{v-1}\gamma^{\mu+v-2}e^{-2\frac{\mu}{\beta}\gamma}\left(\frac{\mu_I}{\overline{\beta}_i} + \frac{\mu\gamma}{\overline{\beta}}\right)^{-2M\mu_I-j-n}.\end{aligned} \tag{4.4}$$

While the CDF and MGF are derived and expressed in the thesis with equations 2.80 and 2.86 and published in equations [P1, eq.28] and [P1, eq.32] respectively. ▪

Thesis 1.3. I identified the effect of CCI on the performance of the dual-hop network, in terms of deriving and analyzing the outage and average error rate probabilities following the MGF approach in [10]. The derived formulas are listed in sections 2.4 in the thesis and published in [P1, section 4]. The outage probability was derived in equation 2.89 in the thesis and published in [P1, eq.34].

While assuming coherent Binary-Phase-Shift-Keying (BPSK) modulation to derive the formula of average error rate probability and represented in equation 2.97 in the thesis and published in [P1, eq.38]. While equations: 2.101, 2.107, 2.109 and 2.111 represents different values for the number of interferes and different values of α and μ parameters, which are published in [P1, eq.40] special cases. Then an analytical analysis approach was applied to analysis the results for different values of number of interferers at the source, destination and relay nodes. ▪

4.2 Impact of co-channel interference on the performance of cooperative diversity systems

Introducing cooperative diversity to the dual-hop replay network, where this technique is used to mitigate the CCI effect when using multiple UAV-assisted to extend and enhance network coverage and data throughput. In this thesis group, we extended the investigation in thesis in section 4.1 which published in paper [P1] by introducing cooperative diversity to the proposed dual-hop network, where we added multiple UAV-assisted acting as relay nodes between the source and destination nodes. The impact of the presence of CCI at the network was identified by deriving the error and outage probabilities of the network over α-μ fading channels, while using the selective combining (SC) schema to get the signal from the best relay link assuming that there is no direct link between the source and destination nodes. In addition, we develop the mathematical formulas for the probability density function (PDF) in addition to the cumulative distribution function (CDF) of the signal-to-interference-and-noise ratio (SINR) of the cooperative diversity network.

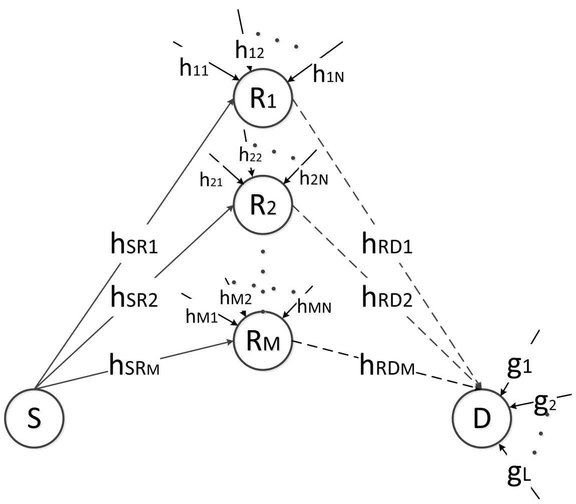

Figure 4.2: Cooperative Diversity Relay Network.

SC technique is used at the destination node D, where the branch with the highest SNR is chosen as the output SNR to be used in the next stage of calculations. The end-to-end Signal-to-noise ratio (SNR) at the combiner output of the destination node is a result of the best-relay SNR, and can be expressed as:

$$\gamma_d = \max_j \left(\gamma_{sr_jd}\right), \tag{4.5}$$

where γ_{sr_jd} is the received SNR from the j-th indirect path ($S \to R_j \to D$), and it can be derived after substituting the value of the amplification gain G_{AF_j} which is given in (4.2), then dividing both the nominator and denominator by N_o^2 then by $\left(1+\sum_{j=1}^{N_i}\gamma_{ji}\right) \times \left(1+\sum_{k=1}^{L}\gamma_k\right)$, the SNR can be derived and simplified as:

$$\gamma_{sr_jd} = \frac{\gamma_{sr_j}^{eff}\gamma_{r_jd}^{eff}}{\gamma_{sr_j}^{eff}+\gamma_{r_jd}^{eff}+1} \quad . \tag{4.6}$$

where the effective SINR for the $S \to R_j$ and the $R_j \to D$ links are defined as:

$$\gamma_{sr_j}^{eff} = \frac{\gamma_{sr_j}}{1+\sum_{i=1}^{N_j}\gamma_{ji}}, \tag{4.7a}$$

$$\gamma_{r_j d}^{eff} = \frac{\gamma_{r_j d}}{1 + \sum_{k=1}^{L} \gamma_k}, \tag{4.7b}$$

To have an attractable mathematical for of the performance metrics as the outage and error probability for the network, we adopted a tight upper bound for γ_{SC} such that:

$$\gamma_d \leq \max_j \left(\min_j \left(\gamma_{sr_j}^{eff}, \gamma_{r_j d}^{eff} \right) \right) \quad . \tag{4.8}$$

Thesis Group 2. Error rate and outage performance were formulated for cooperative diversity relay network over α-μ fading channels in the presence of co-channel interference's (CCI). Where I developed the probability density function (PDF) and the cumulative distribution function (CDF) of the upper bound of the combiner output SINR. The derived expressions for the outage and error probability were also used to identify the effect of CCI on the performance of the cooperative diversity relay network for different values of ($\mu = 1$) and ($\mu = 2$) with the value of ($\alpha = 2$) fading parameter correspondingly, and it's published in [P2].

Thesis 2.1. I derived the statistical characteristics in terms of the PDF and CDF of the best-relay node SINR (γ_{SC}). The CDF of γ_d is denoted by equation 3.10 in the thesis and [P2, eq.10], which is mathematically represented as:

$$F_{\gamma_d}(\gamma) = \prod_{j}^{M} F_{\gamma_j}(\gamma) \tag{4.9}$$

Then I derived the PDF formula, which can then be derived by taking the derivation of the CDF in eq 3.11 in the thesis and [P2, eq.11], and can be denoted in an attractable mathematical formula as:

$$\frac{d}{dx}\left[\prod_{i=1}^{k} f_i(x)\right] = \sum_{i=1}^{k} \left(\frac{d}{dx} f_i(x) \prod_{j \neq i} f_j(x) \right) = \left(\prod_{i=1}^{k} f_i(x) \right) \left(\sum_{i=1}^{k} \frac{f_i'(x)}{f_i(x)} \right) \tag{4.10}$$

The PDF equation is derived and denoted in the thesis in equation 3.13 and [P2, eq.13] respectively. ▪

Thesis 2.2. I derived the outage probability which is considered one of the important measures of the network performance. Analyzing the outage probability is essential to characterize the error performance and reliability of the cooperative diversity network. The outage probability is defined at the output of the selection combiner as the probability at which the SINR falls below a certain threshold value (γ_{th}), and is derived mathematically in equation 3.23 in the thesis and in [P2, eq.14]. The outage probability is denoted by:

$$P_{out} = \Pr(\gamma_d \leq \gamma_{th}) = P_{\gamma_d}(\gamma_{th}) = \int_0^{\gamma_{th}} f_{\gamma_d}(\gamma) d\gamma \tag{4.11}$$

The other important performance measure is the error probability, and mathematically denoted by:

$$\overline{P_e} = \int_0^{\infty} P_b(\gamma)\; f_{\gamma_d}(\gamma)\; d\gamma \tag{4.12}$$

Assuming coherent Binary-Phase-Shift-Keying (BPSK) modulation, I derived a special case of the the average error probability $\overline{P_e}$ which can be upper bounded then can be reduced for identical fading channel with coefficients of $\alpha = 2$ and $\mu = 1$, and using the binomial expansion and some mathematical manipulation, as:

$$\overline{P_e} \leq 2^{M-1} \sum_{k=0}^{M} \binom{M}{k} \left(\frac{\overline{\beta} L}{\overline{\beta} + 2} \right)^k e^{\frac{2\Lambda}{\overline{\beta}} k + \Lambda k} \times E_{2L+1}^{k} \left(\frac{\Lambda}{\overline{\beta}} (\overline{\beta} + 2) \right). \tag{4.13}$$

Where L is the interferes number at the j-th relay which is identical as the same number of interferes at the destination node, and ($\Lambda = \frac{\overline{\beta}_{sr_j}}{\overline{\beta}_j}$) represents the average Signal to Interference Ratio (SIR) at the Relay node. In addition, ($\Upsilon = \frac{\overline{\beta}_{r_j d}}{\overline{\beta}_K}$), is the average SIR at the relay and Destination node respectively. ▪

4.3 Deep Reinforcement Learning for Jointly Resource Allocation and Trajectory Planning in UAV-assisted Networks

One of the challenging optimization problems related to UAV-assisted application is the joint optimization problem of resource allocation and the UAV placement and position while maintaining the battery life of the UAV. UAV-assisted wireless communications were categorized into three main types: UAV-carried eNB or gNB, UAV relaying, and UAV-assisted IoT networks. However, existing systems face limitations due to the UAV's battery life and optimal positioning challenges.

We focus in this thesis group on a primary application of UAVs in communication systems, where UAV can be used during emergencies when the mobile infrastructure is unavailable, and mobile service provision is essential. However, determining the optimal UAV position in the cell area before battery depletion remains complex.

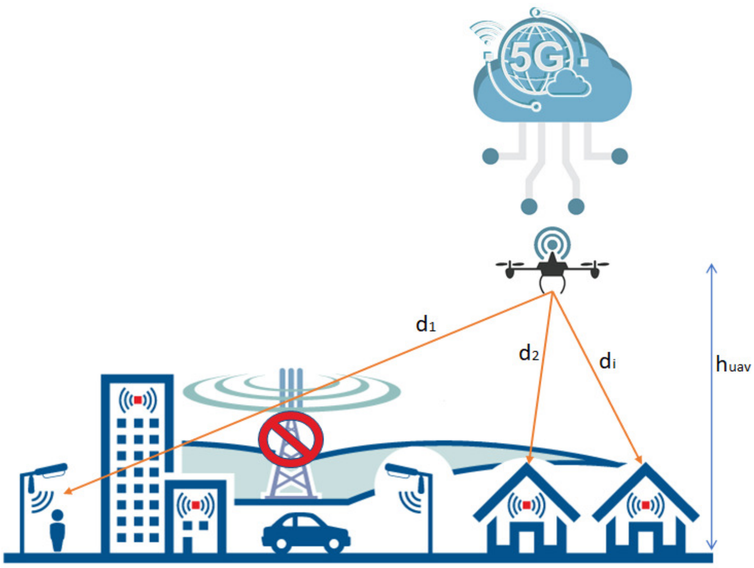

Figure 4.3: UAV emergency model.

We considered a multi-rotor UAV with total energy E_{max} that is flying at a fixed altitude of h_{max} from a base point denoted by $s_0 = (x_0, y_0)$. The UAV has an onboard gNB that will serve K subscribers within a specific area. At the beginning (τ_i) of time slot i, the gNB decides the assignment of Resource Blocks (RB) for each customer according to specific criteria; in our study, we adopt the customer's QoS requirements, and the channel quality, where the gNB can measure the channel quality of each user's device and allocate the RB's based on a minimum requirement to maintain the network performance. We assume that the gNB receives the CQI values. ($CQI(i) = [CQI_{1,i}, CQI_{2,i}, \ldots, CQI_{k,i}]$) of $k = \{1, ..., K\}$ user equipment (UEs) at time instance τ_i where $i = 0, \ldots$, which is in accordance with the time-slot operation of the gNB, so $\tau_{i+1} - \tau_i = \Delta$. At each time step $\tau_i = a \times i \times \Delta$, the UAV decides to continue flying or get back to the base point while monitoring the battery level. For this problem, we apply Reinforcement learning (RL) for flight control as follows:

- At each time step τ_i, the state $s_i = [(x_i, y_i, h_{max}, E_i), [CQI_{k,i}]] \ \ \forall\ k \in [0, K]$ consists of UAV position, which can be denoted by the coordinates (x_i, y_i, h_{max}) and the UAV battery energy level, in addition to the received CQI values, form the UEs $CQI_{k,i} \forall k \in [1, K]$, and the UAV battery level E_i.

- We assume that the altitude of the UAV is fixed in this study, which can lead to the possible actions: backward, forward, left, right, and hovering in the same location and returning to the base point. The action space is $\mathcal{A} == \{L, R, FW, BW, HO, RE\}$.

- The reward function is defined as the logarithmic function for the joint condition between the number of served UEs $U_{i,k}$ and the ratio of the allocated RB $N_{i,k}^{RB}$ to the total RB in each time step, where the reward function is used to maximize the number of served UEs with minimum allocated RB's, and denoted as:

$$r_i = \left(\sum_{k=1}^{K} U_{i,k} \right) \times U_{tot} + \frac{N_{tot}^{RB}}{\sum_{k=1}^{K} N_{i,k}^{RB}}, \tag{4.14}$$

Where the binary variables $U_k \in \{0, 1\}, \forall k$, which is asserted if the UAV succeeded in serving the k^{th} UE, and allocated the required resources to guarantee the minimum throughput required to provide coverage for the cell in emergencies. Otherwise, U_k is set to 0. In this study, we adopt the max CQI scheduling allocation of the UEs, where the UEs with the highest values of CQI are allocated while there are available resource blocks in the radio frame. While the other variable $N_{i,k}^{RB}$, $\forall k$ represent the sum of allocated RB's for the UEs that were allocated successfully and got mobile services in time slot i, the N_{tot}^{RB} represents the total number of RB's in the bandwidth. And finally, U_{tot} denotes the total number of UEs that are requesting the mobile service in a predefined cell area.

Thesis Group 3. I formulated the MDP with (state description, action space, reward function), and applied deep reinforcement learning algorithm (DRL) to optimize communication resource allocation and UAV position collaboratively. RL agent was trained with the Proximal Policy Optimization (PPO) algorithm to solve the non-convex joint optimization problem. Published in [P3].

Thesis 3.1. With the previously described MDP, the DRL agent is capable of finding the optimal UAV position where the allocated RB's is the minimum and the number of served UE is the maximum in the cell, at the same time, taking into account the battery life of the UAV and different cell area sizes and UE numbers. ∎

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[P1] A. M. J. Jwaifel, I. Ghareeb, and S. Shaltaf, "Impact of co-channel interference on performance of dual-hop wireless ad hoc networks over α-μ fading channels," *International Journal of Communication Systems*, vol. 33, no. 14, p. e4500, 2020.

[P2] A. M. Jwaifel, I. Ghareeb, and T. Van Do, "Impact of Co-channel Interference on the Performance of Cooperative Diversity Systems over α-μ Fading Channels," *International Journal of Wireless Information Networks*, 2022.

[P3] A. M. Jwaifel and T. Van Do, "Deep reinforcement learning for jointly resource allocation and trajectory planning in uav-assisted networks," in *Computational Collective Intelligence* (N. T. Nguyen, J. Botzheim, L. Gulyás, M. Núñez, J. Treur, G. Vossen, and A. Kozierkiewicz, eds.), (Cham), pp. 71–83, Springer Nature Switzerland, 2023.

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Glossary

E_S The energy of the transmitted signal from the Source node

d_S The desired transmitted data from the source node with unit energy

h_{sr} The channel flat fading coefficient of $S \rightarrow R$ link

h_i The α-μ flat fading coefficient of the $i-$th interference channel at the relay node

x_i The α-μ flat fading coefficient of the $i-$th interference channel at the relay node

E_i The $i-$th interference channel energy received at the relay node

d_i The transmitted data from relay node with unit energy

n_{sr} The Additive White Gaussian Noise at the relay node

E_R The energy of the transmitted signal from the Relay node

h_{rd} The channel flat fading coefficient of $D \rightarrow D$ link

E_k The k-th interference channel energy received at the destination node

g_k The α-μ flat fading coefficient of the k-th interference channel at the destination node

d_k The k-th co-channel interferer's data with unit energy at the destination

n_{rd} The Additive White Gaussian Noise at the destination node

γ_{SC} The SINR at the combiner output of the destination node which is the result of the best-relay SINR.

γ_{sr_jd} The SINR for the j-th indirect path ($S \to R_j \to D$).

γ_{sr_j} The SINR for the source and the j-th relay node link($S \to R_j$).

γ_{r_jd} The SINR for the j-th relay node and the destination node link($R_j \to D$).

γ_{ji} The SINR for the i-th interfere at the j-th relay node.

γ_{g_k} The SINR of the k-th interfere at the destination node.

$F_{\gamma_{SC}}$ The $S \to R \to D$ link average SINR accumulative deinsity function (CDF).

$\overline{\beta}_{r_jd}$ The average SINR of the j-th relay to the destination $R_j \to D$ link.

$\overline{\beta}_{I_j}$ The average SIR at the j-th relay node from the i-th interferes.

$\overline{\beta}_{sr_j}$ The average SINR from the source node to the j-th relay node $S \to R_j$.

$\overline{\beta}_K$ The average SIR for the k-th interferes at the destination node.

μ_{I_j} The α-μ coefficient for the j-th reply node.

μ_k The α-μ coefficient for the k-th interfere at the destination node.

$f_{\gamma_{SC}}$ The $S \to R \to D$ link average SINR density function (pdf).

P_{out} The outage probability.

E_{max} The total energy of the multi-rotor UAV battery.

h_{max} The UAV altitude (m).

s_0 The UAV start point in the grid.

k The total number of subscribers that were located the served cell.

τ_i The i-th time slot.

$CQI(k, i)$ The i-th time slot CQI value of the k-th UE.

$U_{i,k}$ The i-th time slot CQI value of the k-th UE.

r_i The i-th reward value.

N_{tot}^{UE} The total number of UEs that are requesting the mobile service in a certain cell area.

N_{tot}^{RB} The total number of RBs in the bandwidth.

$N_{i,k}^{RB}$ The sum of allocated RBs for the UEs that were allocated successfully and got mobile services in time slot i.

E_i The UAV battery energy level value at each time slot.

Acronyms

5G	Fifth-generation mobile system
6G	Sixth-generation mobile system
AF	Amplify and forward
AWGN	Additive white gaussian noise
BER	Bit error rate
BPSK	Binary phase shift keying
CCI	Co-channel interference
CDF	Commutative distribution function
CSI	Channel state information
dB	Decibels
DF	Decode and forward
DPSK	Differential phase shift keying
ECC	Error-Correcting Codes
EGC	Equal gain combining
eNB	Evolved node-b
GCD	Greatest Common Divisor
gNB	Next-generation node-b
I.I.D.	Independent and identically distributed
IEEE	Institute of electrical and electronics engineer
INID	Independent but not identically distributed

ISI	Inter-symbol Interference
LoS	Line-of-sight
LTE	Long term evolution
MCS	Modulation and coding scheme
MDP	Markov decision problem
MGF	Moment generating function
ML	Machine learning
MRC	Maximal ratio combining
NR	New radio
PDF	Probability density function
PPO	Proximal policy optimization
PRB	Physical resource block
QoS	Quality of service
R-D	Relay to destination link
RB	Resource block
RL	Reinforcement learning
S-R	Source to relay link
SC	Selective combining
SINR	Signal to interference plus noise ratio
SNR	Signal to noise ratio
TBS	Transport block size
UAV	Unmanned aerial vehicles
UE	User equipment