Machine Learning-Based Power Allocation for Covert Communication in LEO-UAV Cooperative Networks*

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Abstract

This paper proposes a machine learning-based power allocation scheme for covert communication in low earth orbit (LEO)-unmanned aerial vehicle (UAV) cooperative networks. By exploiting the wide service coverage of the LEO satellite and the flexibility of the UAV, the proposed scheme enhances covert communication performance while employing machine learning to reduce the computational complexity of the power allocation process. Simulation results show that the proposed scheme attains performance close to that of the near-optimal scheme.

Keywords: Low earth orbit (LEO) satellite communications, unmanned aerial vehicle (UAV) cooperative jamming, covert communication, power allocation, machine learning

1 Introduction

As secure communication has become one of the fundamental research topics in wireless communication systems, research on physical layer security (PLS) has been actively conducted. However, one of the major limitations of channel information–based security methods is their vulnerability when the channel information is exposed, which significantly weakens the overall security performance. Motivated by this drawback, covert communication, which aims to conceal the very existence of a transmission and render it undetectable by unintended observers, has recently emerged as a promising paradigm for secure wireless communications [1]. In this context, the authors in [2] propose a scheme that employs full-duplex decode-and-forward (DF) user relaying to achieve perfect cancellation of covert signals at the warden. Recently, covert communication has also been extended from terrestrial networks to low earth orbit (LEO) satellite communication systems. In [3], the authors propose a covert communication scheme that integrates multi-tier LEO satellite networks with unmanned aerial vehicles (UAVs), employing a game-theoretic analysis to simultaneously enhance transmission reliability and covertness against ground-based wardens. LEO–UAV integrated systems have attracted significant attention due to their ability to provide both wide service coverage and high flexibility. Along this line, the authors in [4] investigate channel prediction in UAV–LEO links and propose a lightweight channel prediction network based on multilayer perceptrons (MLPs), which improves prediction accuracy while reducing computational complexity.

Motivated by these studies, in this paper, we propose a machine learning-based power allocation scheme for covert communication in LEO-UAV cooperative networks. The scheme exploits

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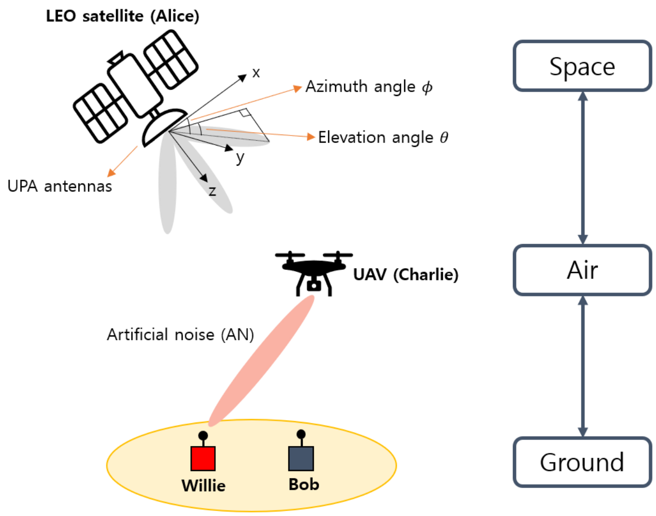

Figure 1: Our system model.

the wide coverage of LEO satellite and the flexibility of UAV to improve covert communication performance, while employing a machine learning to reduce the computational complexity of power allocation. The UAV acts as a cooperative jammer by transmitting artificial noise (AN) to enhance covertness, while the learning model adopts a deep neural network (DNN) architecture. Simulation results show that the proposed scheme achieves performance close to a near-optimal scheme with lower the computational complexity.

The remainder of this paper is organized as follows. In Section II, we describe the system model and formulate the problem of covert communication. Section III presents the proposed machine learning-based power allocation scheme, and Section IV evaluates its performance through simulations. Finally, Section V concludes the paper.

2 System model

Figure 1 illustrates the considered system model. We consider a LEO-UAV cooperative network consisting of one LEO satellite (Alice) equipped with N_U uniform planar array (UPA) antennas, one UAV (Charlie) equipped with a two-element uniform linear array (ULA) and acting as a cooperative jammer, one legitimate user (Bob) with a single antenna, and one warden (Willie) with a single antenna. The UPA antennas at the LEO satellite have a dimension of $N_U = N_x \times N_y$, where N_x and N_y denote the number of antennas along the x-axis and y-axis, respectively. Alice employs maximum ratio transmission (MRT) beamforming to serve Bob, while Charlie adopts zero-forcing (ZF) beamforming to transmit artificial noise (AN) toward Willie. The channel from Alice to Bob is denoted by $\mathbf{h}_{AB} \in \mathbb{C}^{N_U \times 1}$, that from Alice to Willie by $\mathbf{h}_{AW} \in \mathbb{C}^{N_U \times 1}$, that from Charlie to Bob by $\mathbf{h}_{CB} \in \mathbb{C}^{2\times 1}$, and that from Charlie to Willie by $\mathbf{h}_{CW} \in \mathbb{C}^{2\times 1}$. We assume that the channels associated with Alice and Charlie follow a Rician fading channel model. Accordingly, the channels from Alice to Bob ($\mathbf{h}_{AB}$) and from Alice to Willie

($\mathbf{h}_{AW}$) can be expressed as

$$\begin{aligned} \mathbf{h}_{AB} &= \sqrt{\frac{K_{AB}}{K_{AB}+1}}\,\mathbf{h}_{AB}^{\texttt{LoS}} + \sqrt{\frac{1}{K_{AB}+1}}\,\mathbf{h}_{AB}^{\texttt{NLoS}}, \\ \mathbf{h}_{AW} &= \sqrt{\frac{K_{AW}}{K_{AW}+1}}\,\mathbf{h}_{AW}^{\texttt{LoS}} + \sqrt{\frac{1}{K_{AW}+1}}\,\mathbf{h}_{AW}^{\texttt{NLoS}}, \end{aligned} \tag{1}$$

where K_{AB} and K_{AW} denote the Rician K-factors for the Alice-Bob and Alice-Willie links, respectively. The components $\mathbf{h}_{AB}^{\texttt{LoS}}$ and $\mathbf{h}_{AW}^{\texttt{LoS}}$ represent the line-of-sight (LoS) part, while $\mathbf{h}_{AB}^{\texttt{NLoS}}$ and $\mathbf{h}_{AW}^{\texttt{NLoS}}$ denote the non-line-of sight(NLoS) part modeled as a Rayleigh fading channel. The LoS component of Alice's channels are given by

$$\begin{aligned} \mathbf{h}_{AB}^{\texttt{LoS}} &= \mathbf{a}(\phi_{AB}, \theta_{AB}), \\ \mathbf{h}_{AW}^{\texttt{LoS}} &= \mathbf{a}(\phi_{AW}, \theta_{AW}), \end{aligned} \tag{2}$$

where $\mathbf{a}(\phi_{AB}, \theta_{AB})$ and $\mathbf{a}(\phi_{AW}, \theta_{AW})$ denote the array steering vectors of Alice's UPA toward the directions specified by the azimuth angle ϕ and elevation angle θ. Similarly, the channels from Charlie to Bob ($\mathbf{h}_{CB}$) and from Charlie to Willie ($\mathbf{h}_{CW}$) are modeled as Rician fading channels and can be expressed as

$$\begin{aligned} \mathbf{h}_{CB} &= \sqrt{\frac{K_{CB}}{K_{CB}+1}}\,\mathbf{h}_{CB}^{\texttt{LoS}} + \sqrt{\frac{1}{K_{CB}+1}}\,\mathbf{h}_{CB}^{\texttt{NLoS}}, \\ \mathbf{h}_{CW} &= \sqrt{\frac{K_{CW}}{K_{CW}+1}}\,\mathbf{h}_{CW}^{\texttt{LoS}} + \sqrt{\frac{1}{K_{CW}+1}}\,\mathbf{h}_{CW}^{\texttt{NLoS}}, \end{aligned} \tag{3}$$

where K_{CB} and K_{CW} denote the Rician K-factors for the Charlie-Bob and Charlie-Willie links, respectively. The LoS components of Charlie's channels are given by

$$\begin{aligned} \mathbf{h}_{CB}^{\texttt{LoS}} &= \mathbf{a}(\phi_{CB}), \\ \mathbf{h}_{CW}^{\texttt{LoS}} &= \mathbf{a}(\phi_{CW}), \end{aligned} \tag{4}$$

where $\mathbf{a}(\phi_{CB})$ and $\mathbf{a}(\phi_{CW})$ denote the array steering vectors of Charlie's two-element ULA, which depend only on the azimuth angle. Therefore, the transmit signals of Alice and Charlie are given as follows:

$$\begin{aligned} \mathbf{x}_A &= \mathbf{w}_A \sqrt{\alpha_A P_A} s, \\ \mathbf{x}_C &= \mathbf{w}_C \sqrt{\alpha_C P_C} \mathbf{z}, \quad \mathbf{z} \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_2) \end{aligned} \tag{5}$$

where $\mathbf{w}_A \in \mathbb{C}^{N_U \times 1}$ and $\mathbf{w}_C \in \mathbb{C}^{2\times 1}$ denote the beamforming vector of Alice and Charlie, respectively. Also, P_A and P_C represent the total transmit powers of Alice and Charlie, and $\alpha_A \in (0, 1)$ and $\alpha_C \in (0, 1)$ are the corresponding power allocation coefficients. The information signal transmitted by Alice is denoted by s, and the AN vector generated by Charlie is denoted by $\mathbf{z}$. The received signals at Bob and Willie can be expressed as follows:

$$\begin{aligned} y_B &= \mathbf{h}_{AB}^{\dagger} \mathbf{x}_A + \mathbf{h}_{CB}^{\dagger} \mathbf{x}_C + n_B \\ y_W &= \mathbf{h}_{AW}^{\dagger} \mathbf{x}_A + \mathbf{h}_{CW}^{\dagger} \mathbf{x}_C + n_W, \end{aligned} \tag{6}$$

where $n_B, n_W \in \mathbb{C}^{1\times 1}$ represent circularly symmetric complex Gaussian noise with zero mean and unit variance at Bob and Willie, i.e., $n_U, n_E \sim \mathcal{CN}(0, 1)$. Here, since Charlie employs ZF beamforming to transmit AN while nulling interference at Bob, we have $\mathbf{h}_{CB}^{\dagger}\mathbf{x}_C = 0$. Then, Bob's signal-to-interference-plus-noise ratio (SINR) becomes

$$\mathsf{SINR}_B = \frac{\alpha_A P_A |\mathbf{h}_{AB}^{\dagger}\mathbf{w}_A|^2}{\alpha_C P_C |\mathbf{h}_{CB}^{\dagger}\mathbf{w}_C|^2 + 1} = \alpha_A P_A |\mathbf{h}_{AB}^{\dagger}\mathbf{w}_A|^2. \tag{7}$$

Based on this SINR, the achievable covert rate at Bob can be expressed as

$$\mathsf{R}_c = \log_2(1 + \mathsf{SINR}_B). \tag{8}$$

During this process, Willie performs energy detection over B blocks to determine whether Alice is transmitting. Accordingly, the binary hypothesis test is formulated as

$$\begin{cases} \mathcal{H}_0: & y_W = \mathbf{h}_{CW}^{\dagger}\mathbf{x}_C + n_W, \quad \text{(Alice is silent)} \\ \mathcal{H}_1: & y_W = \mathbf{h}_{AW}^{\dagger}\mathbf{x}_A + \mathbf{h}_{CW}^{\dagger}\mathbf{x}_C + n_W, \quad \text{(Alice is active)} \end{cases} \tag{9}$$

Here, P_{FA} denote the false alarm probability (i.e., Willie deciding $\mathcal{H}_1$ when Alice is silent), and P_{MD} denotes the miss detection probability (i.e., Willie deciding $\mathcal{H}_0$ when Alice is active). Therefore, the total detection error probability at Willie is defined as

$$\xi = P_{FA} + P_{MD}. \tag{10}$$

To ensure covertness, when the allowable detection error threshold is $\epsilon(0 \le \epsilon \le 1)$, the following condition must hold:

$$\xi \ge 1 - \epsilon. \tag{11}$$

Since the total detection error probability depends on Alice's transmit power and Charlie's artificial noise, the covertness condition in (11) can be reformulated into the following power constraint. Consequently, Alice's transmit power must satisfy the covert communication constraint given by

$$(\alpha_A P_A |\mathbf{h}_{AW}^{\dagger}\mathbf{w}_A|^2)^2 \le 4B\epsilon^2(1 + \alpha_C P_C |\mathbf{h}_{CW}^{\dagger}\mathbf{w}_C|^2)^2 \tag{12}$$

If this constraint is not satisfied, Willie can detect Alice's transmission with high probability, and thus the covert rate is set to zero (i.e., $\mathsf{R}_c = 0$). However, it is computationally intractable to search over all continuous values of α_A and α_C between 0 and 1. Therefore, in this paper, we discretize the power allocation coefficients with a step size of $\gamma(0 \le \gamma \le 1)$ and perform a grid search to determine the values of α_A and α_C that maximize the covert rate. The set of possible power allocation coefficients is given by

$$Q = \{0, \gamma, 2\gamma, \ldots, 1\}. \tag{13}$$

Accordingly, the number of possible power allocation coefficient combinations of α_A and α_C is $|Q|^2 = ((1/\gamma) + 1)^2$. Based on this discretized set Q, the optimal power allocation coefficient combination is obtained by solving the following problem:

$$\begin{aligned} \underset{\alpha_A, \alpha_C \in Q}{\text{maximize}} \quad & \mathsf{R}_c(\alpha_A, \alpha_C) \\ \text{s.t.} \quad & (\alpha_A P_A |\mathbf{h}_{AW}^{\dagger}\mathbf{w}_A|^2)^2 \le 4B\epsilon^2(1 + \alpha_C P_C |\mathbf{h}_{CW}^{\dagger}\mathbf{w}_C|^2)^2, \\ & 0 \le \alpha_A, \alpha_C \le 1. \end{aligned} \tag{14}$$

However, the obtained optimal power allocation coefficient combination is derived within the discretized set rather than the entire continuous range, and is therefore defined as a near-optimal power allocation coefficient combination in this paper. On the other hand, even in this

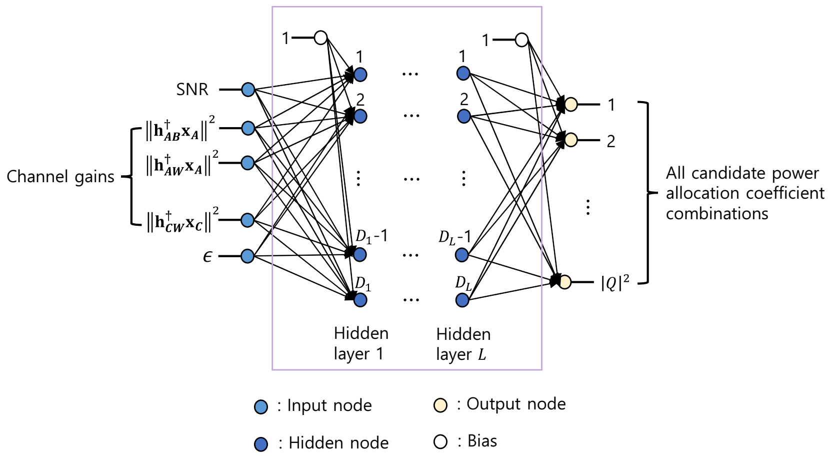

Figure 2: The architecture of the proposed machine learning model.

discretized search approach, the number of possible power allocation coefficient combinations increases rapidly as the network size grows or the step size γ becomes smaller, leading to a significant rise in computational complexity. To address this issue, we propose a machine learning-based scheme that identifies a near-optimal power allocation coefficient combination without exhaustively searching through all possible candidates.

3 Proposed machine learning-based power allocation scheme for covert LEO-UAV cooperative networks

In this section, we propose machine learning-based power allocation scheme for covert LEO-UAV cooperative networks. We first explain how the learning model is employed within the power allocation process, and then describe the architecture of the proposed model in detail.

3.1 Basic idea

The objective of the proposed scheme is to reduce the computational complexity of finding the near-optimal power allocation coefficient combination that maximizes the covert rate by employing a machine learning model. Although the conventional scheme is straightforward, it requires an exhaustive search over all possible combinations, and the computational burden increases rapidly as the step size γ becomes smaller. In contrast, the proposed scheme can predict a near-optimal power allocation coefficient combination with significantly lower computational complexity without exhaustively exploring the entire search space. Specifically, the proposed model takes as input the channel gain between Alice and Bob $|\mathbf{h}_{AB}^{\dagger}\mathbf{x}_A|^2$, the channel gain between Alice and Willie $|\mathbf{h}_{AW}^{\dagger}\mathbf{x}_A|^2$, the channel gain between Charlie and Willie $|\mathbf{h}_{CW}^{\dagger}\mathbf{x}_C|^2$, and the allowable detection error threshold ϵ, and uses them to predict the near-optimal power allocation coefficient combination.

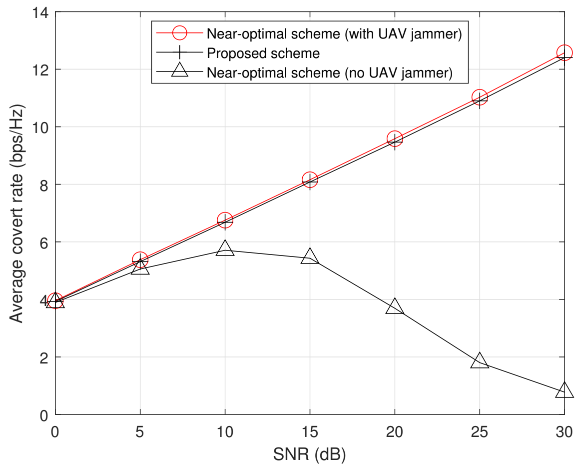

Figure 3: The average covert rate of various schemes.

3.2 Architecture of the proposed machine learning model

Figure 2 illustrates the architecture of the proposed machine learning model. The model adopts a DNN structure consisting of L hidden layers with D_l hidden nodes in the lth hidden layer, five input nodes, and $|Q|^2 = ((1/\gamma) + 1)^2$ output nodes. Here, the input nodes consist of the signal-to-noise ratio (SNR), the channel gain between Alice and Bob $|\mathbf{h}_{AB}^{\dagger}\mathbf{x}_A|^2$, the channel gain between Alice and Willie $|\mathbf{h}_{AW}^{\dagger}\mathbf{x}_A|^2$, the channel gain between Charlie and Willie $|\mathbf{h}_{CW}^{\dagger}\mathbf{x}_C|^2$, and the allowable detection error threshold ϵ. Since the task is to select one near-optimal combination, we employ the rectified linear unit (ReLU) function as the activation function for the hidden nodes and the softmax function for the output nodes. For the training process, the categorical cross-entropy function is adopted as the loss function, which is given by

$$\xi = -\sum_{i=1}^{|Q|^2} \varphi_i \log(c_i), \tag{15}$$

where φ_i represents the one-hot encoded label and c_i denotes the predicted probability obtained through the softmax function. In addition, early stopping was applied to prevent overfitting, and the adaptive moment estimation (Adam) algorithm was employed as the optimization algorithm.

4 Numerical results

In this section, we evaluate the performance of the proposed scheme by comparing it with a near-optimal scheme that employs a grid search method (i.e., exhaustive search over the discretized set) to predict the near-optimal power allocation coefficient combination. We consider an environment where Alice is equipped with a 4×4 UPA antenna array (i.e., $N_x = N_y = 4$), and the Rician K-factors of Alice and Charlie are set to 10 (i.e., $K_{AB} = K_{AW} = K_{CB} = K_{CW} = 10$). Willie is assumed to perform energy detection over 500 blocks ($B = 500$) with an allowable detection error threshold of 0.05 ($\epsilon = 0.05$). The discretization step size is set to 0.1 ($\gamma = 0.1$). Accordingly, the proposed model has five input nodes and a total of 121 output nodes ($|Q|^2 = 121$). We consider a DNN model with three hidden layers, where the first, second, and third layers consist of 300, 500, and 500 hidden nodes, respectively, i.e., $(D_1, D_2, D_3) = (300, 500, 500)$. For training, 7×10^4 samples are generated, of which 80% are used for training and 20% for validation. The trained model is then evaluated using 7×10^3 test samples. Figure 3 shows the comparison of the average covert rate between the proposed scheme and the near-optimal scheme obtained by grid search. Here, *Near-optimal scheme (with UAV jammer)* refers to the performance of the near-optimal scheme with Charlie (UAV jammer) present, while *Near-optimal scheme (no UAV jammer)* refers to the case where only Alice is present without Charlie. The simulations are conducted using MATLAB and the TensorFlow framework, where MATLAB is used to generate the training and test samples, and TensorFlow is used to implement the DNN architecture. As shown in Figure. 3, the proposed scheme achieves performance close to that of the near-optimal scheme obtained via grid search. Moreover, in the absence of Charlie, the average covert rate decreases beyond 10 dB. The computational complexity of the proposed machine learning-based scheme is given by

$$O\left(5D_1 + \sum_{l=1}^{L-1} D_l D_{l+1} + D_L |Q|^2\right), \tag{16}$$

while that of the near-optimal scheme is

$$O(|Q|^2). \tag{17}$$

When the discretization step size is $\gamma = 0.1$, only 121 combinations need to be examined. However, if $\gamma = 0.01$, the number of possible combinations increases dramatically to $10,201$. In this case, while the grid search method must exhaustively evaluate all combinations, the proposed scheme only requires a single inference of the trained model, thereby achieving much lower computational complexity.

5 Conclusions

In this paper, we proposed a machine learning-based power allocation scheme for covert communication in LEO-UAV cooperative networks. The proposed scheme enhances covert communication performance by harnessing the cooperation between the LEO satellite and the UAV, while reducing the computational complexity of finding the power allocation coefficient combination that maximizes the covert rate among all possible LEO and UAV power allocation coefficient combinations through the use of machine learning. Numerical results demonstrate that the proposed scheme achieves nearly the same performance as the near-optimal scheme, while reducing computational complexity.

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References

[1] X. Chen, J. An, Z. Xiong, C. Xing, N. Zhao, F. R. Yu, and A. Nallanathan, "Covert communications: A comprehensive survey," *IEEE Commun. Surveys Tuts.*, vol. 25, no. 2, pp. 1173–1210, 2nd Quart., 2023.

[2] J. Y. Ryu and J. H. Lee, "Covert communications via full-duplex user relaying," *Sensors*, vol. 25, no. 12, Art. no. 3614, Jun. 2025.

[3] S. Feng, X. Lu, S. Sun, E. Hossain, G. Wei, and Z. Ni, "Covert communication in large-scale multi-tier LEO satellite networks," *IEEE Trans. Mobile Comput.*, vol. 23, no. 12, pp. 11576–11587, Dec. 2024.

[4] J. Wang, S. Gong, J. Xiao, P. Guo, J. Wang, W. Xie, and X. Li, "A lightweight channel prediction network for UAV-LEO satellite communications," *IEEE Wireless Commun. Lett.*, vol. 14, no. 1, pp. 113–117, Jan. 2025.