RESEARCH ARTICLE

Joint Design of Energy-Efficient MIMO Receiver and Power Allocation for Spatial NOMA in Miniature UAV-Assisted IoT Networks

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Abstract

The work presents a joint design framework that combines an energy-efficient MIMO receiver architecture with an optimized power allocation strategy for spatial NOMA in miniature UAV-assisted IoT networks. Specifically, we design a low-power receiver using spatial modulation and intelligent transmit antenna selection to minimize energy usage. Simultaneously, a dynamic power allocation scheme is developed to ensure fairness by allowing all users to act as active data users in different time slots. The air-to-ground channel is modeled by considering UAV altitude, mobility, and probabilistic line-of-sight characteristics. Simulation results demonstrate that at a UAV altitude of 50 meters, the proposed method achieves a peak energy efficiency of approximately 7.8 bits/Joule, compared to 6.0 bits/Joule for traditional NOMA schemes. The system also maintains a target user data rate of 2 bits/s/Hz and performs optimally at a transmit power of 20 dBm and UAV velocity of 5 m/s. These results highlight the effectiveness of jointly optimizing receiver design, power control, and UAV parameters to achieve sustainable and high-performance communication in future 6G-enabled IoT networks.

Keywords: wireless network, 5G, AI, network virtualization, 6G.

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1 Introduction

The exponential expansion of the Internet of Things (IoT) has resulted in a substantial increase in the number of interconnected devices, thereby intensifying the demand for communication networks that are both energy-efficient and reliable. IoT networks are being widely adopted across diverse domains such as smart cities, agriculture, healthcare, and industrial automation, each of which necessitates real-time data transmission under varying communication and energy constraints [1]. A fundamental challenge in these applications is ensuring energy-efficient communication, particularly in scenarios where devices operate under strict resource limitations [2]. To address these challenges, Unmanned Aerial Vehicle (UAV)-assisted IoT

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networks have emerged as a viable solution. UAVs, commonly known as drones, offer a flexible and mobile communication infrastructure, capable of providing coverage and data relaying in areas lacking terrestrial network infrastructure or where conventional communication methods prove inefficient [3]. These miniature UAVs, functioning as mobile base stations, can dynamically enhance network coverage. However, the overall performance of UAV-assisted IoT systems is significantly influenced by the choice of communication technology, the UAVs' power requirements, and their inherent energy constraints [4]. The integration of advanced wireless communication techniques is crucial for enhancing the performance of such networks [5]. One such technique is Multiple Input Multiple Output (MIMO), which utilizes multiple antennas at both the transmitter and receiver ends to simultaneously transmit multiple data streams over the same frequency spectrum [6]. This approach enhances spectral efficiency, data throughput, and link reliability. However, deploying MIMO within UAV-based systems introduces complexities, primarily due to the increased power demands associated with managing multiple antennas, which may exceed the limited energy reserves of UAV platforms [7]. In parallel, Non-Orthogonal Multiple Access (NOMA) has gained prominence as a spectrum-efficient access technique, particularly well-suited to scenarios with limited bandwidth and a high density of users [8]. Unlike traditional Orthogonal Multiple Access (OMA) methods that assign dedicated time or frequency resources to each user, NOMA allows multiple users to access the same time-frequency resources simultaneously by assigning different power levels to their signals[9]. This superposition coding enables more efficient utilization of the available spectrum and is particularly advantageous in UAV-assisted networks with numerous IoT devices [10]. Power allocation plays a critical role in the optimal functioning of MIMO and NOMA systems. Effective power distribution strategies can improve the signal-to-noise ratio (SNR), reduce interference, and minimize energy consumption—factors that are especially crucial in energy-constrained UAV systems [11]. In this context, power control strategies are not only essential for maintaining communication reliability but also for prolonging the operational time of UAVs, thereby improving network sustainability [12].These strategies are particularly vital in challenging environments, such as high-altitude operations or urban areas with complex signal propagation characteristics [13]. This research advocates for the joint design of energy-efficient MIMO receiver architectures and power allocation schemes tailored for spatial NOMA in UAV-assisted IoT networks [14]. By simultaneously optimizing receiver design to reduce energy consumption and developing intelligent power allocation strategies for NOMA, the proposed framework aims to enhance the overall energy and spectral efficiency of the system [15]. Such a co-design approach is essential for achieving scalable, sustainable, and high-performance communication in UAV-based IoT applications [16]. Amid the growing demand for always-on connectivity and the expanding scale of IoT deployments, this study explores the potential of integrating advanced technologies into a cohesive framework that maximizes communication performance and energy efficiency [17]. The synergistic combination of MIMO, NOMA, and optimized power control within UAV-assisted environments offers a promising pathway toward overcoming the limitations of conventional systems [18]. This work contributes to the ongoing development of next-generation IoT networks by providing insights into how joint design methodologies can facilitate the practical and sustainable deployment of UAV-enabled communication infrastructures [19].

2 Related Work

2.1 Studies on MIMO

The author [20] investigates a large-scale MIMO system with energy-harvesting receivers. It uses energy beamforming to enhance long-distance power transfer, optimizing transfer time and transmit power to maximize energy efficiency under QoS constraints. Numerical results confirm the effectiveness of the proposed scheme. The study [21] presents an EE-optimized precoder for MIMO wiretap channels under secrecy and power constraints. A convexified problem is solved iteratively, with extensions for imperfect CSI. Results show improved EE over existing methods. The author [22] proposes an energy-efficient VLC solution for 6G using RoF to process SM-MIMO signals, cutting MIMO DSP power use. An all-optical PI strategy reduces channel correlation without DAC/ADC. The design lowers cost with minimal (1.5 dB) performance loss. The author [23] presents an analytical framework for RIS-integrated MIMO-FSO systems, tackling turbulence, misalignment, and attenuation. It derives closed-form metrics for outage, BER, and energy efficiency, and optimizes

RIS placement and diversity combining. Simulations confirm its robustness and energy efficiency for future optical networks.

2.2 Studies on NOMA and MIMO-NOMA

The study [24] author analyzes PAPR issues in MIMO-NOMA systems and reviews reduction methods like PTS, SLM, TR, and ACE. It proposes a hybrid PTS-TR technique, which MATLAB simulations show outperforms existing approaches.[8] proposes RISP-PD-NOMA and RISP-Q-NOMA systems for RIS-assisted PD-NOMA networks, assigning fixed RIS units to users. Closed-form metrics are derived under Rician fading. RISP-PD-NOMA excels with perfect SIC, while RISP-Q-NOMA performs better under imperfect SIC. Numerical results validate the superiority of RISP-Q-NOMA.[25] proposes a decision tree-based signal detection method for downlink MIMO-NOMA in 5G, enhancing reliability and efficiency. The study [26] proposes a GLSIC-based signal processing framework for massive MIMO-NOMA in B5G/6G, grouping users by distance to reduce inter-group interference. It derives the uplink sum-rate considering channel estimation errors and imperfect GLSIC. Results show superior performance over user-level SIC methods. Simulations over Rayleigh and Rician channels show improved performance, with reduced SIC complexity and latency. The author [26] proposes a GLSIC-based signal processing framework for massive MIMO-NOMA in B5G/6G, grouping users by distance to reduce inter-group interference. It derives the uplink sum-rate considering channel estimation errors and imperfect GLSIC. Results show superior performance over user-level SIC methods.The authors [27] analyzes MIMO-NOMA integration for 5G, highlighting its ability to boost spectral efficiency and data rates by combining power-domain user multiplexing (NOMA) with spatial multiplexing (MIMO). The study evaluates system performance in terms of SNR and achievable data rate. The study [?] explores MIMO-NOMA techniques to enhance spectral efficiency and user capacity through power-domain multiplexing. Superposition coding is used in the uplink, and SIC in the downlink. User pairing and cluster formation strategies based on base station antennas are analyzed to improve performance.

2.3 Studies on UAV

The authors [28] proposes a method to improve anti-jamming in UAV-assisted data collection under multi-jammer attacks and imperfect CSI. The optimization problem, covering data collection, power control, and UAV trajectory, is solved using successive convex approximation (SCA). Simulations show superior performance compared to existing methods. The study [29] addresses joint user association and UAV location optimization to maximize data rates in UAV-aided communications. The problem is formulated as a MINCOP and solved with an iterative algorithm using successive convex approximation. The proposed method converges and outperforms existing approaches.The study [30] presents a channel model for UAV-enabled communication systems, considering UAV wobble and varying effective apertures (EA) due to pitch and yaw. It derives expressions for ASNR, showing that wobble degrades performance and increasing antenna elements doesn't improve ASNR. Neglecting EA results in significant overestimation of ASNR. The study [31] proposes a joint trajectory and communication scheduling scheme for UAV-enabled wireless caching networks, modeled as an ergodic stochastic differential game (SDG) to optimize users' QoE. A decentralized solution is derived using mean-field analysis, and a DNN is employed to learn the optimal control online. Simulation results show superior performance over existing methods.

3 System Model

In future 6G-enabled non-terrestrial networks, unmanned aerial vehicles (UAVs) are expected to function as aerial communication platforms, providing line-of-sight (LoS) connectivity to ground users. This study investigates the implementation of spatial non-orthogonal multiple access (S-NOMA) in UAV-assisted IoT networks to enhance energy efficiency (EE), reduce power consumption, and ultimately improve the endurance of UAV-based communication systems. As depicted in Figure 1, a diverse set of users ranging from mobile devices to IoT nodes operate within the UAV's coverage area. In the considered downlink scenario, the UAV is equipped with N_T transmit antennas, although only one antenna is active at any given time slot. Each user terminal is equipped with N_R receive antennas. By utilizing the NOMA technique, users are grouped and their signals are multiplexed in the power domain. The UAV's transmitted signal consists of two main components: the first is transmitted directly through the spatial domain via the selected active antenna, while the second is formed by superimposing multiple user signals in accordance with NOMA principles. Even at high speeds, 200 km/h, a 2×2 MIMO system

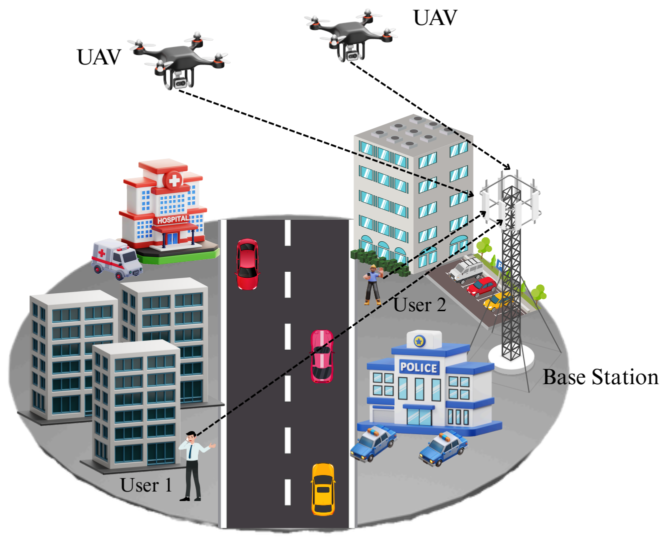

Figure 1. System model illustrating the detection of MIMO signals.

maintains a significant degree of temporal correlation over a 50 μs period. Temporal correlation is typically quantified using the channel coherence time.

3.1 Proposed S-NOMA

The operational framework of the proposed S-NOMA scheme is depicted. Users within a group are labeled as U_1 to U_m. A subset of each user's bits is allocated for determining the active transmit antenna. Given N_T transmit antennas at the UAV, the number of bits used for transmit antenna selection (TAS) is less than $\log_2(N_T)$. The remaining bits are combined using power-domain NOMA to form a superimposed signal, which is then transmitted via the selected antenna. At the receiver side, signal detection is performed using a combination of maximum likelihood (ML) detection and successive interference cancellation (SIC). Through the integration of spatial diversity and NOMA principles, the proposed S-NOMA technique provides enhanced spectral efficiency and performance gains for all users in the network.

3.2 UAV Channel Model

The air-to-ground (A2G) communication channel between a UAV and ground users exhibits distinct characteristics compared to traditional terrestrial channels. These variations are primarily influenced by the UAV's altitude and the angle of elevation relative to the users. Both line-of-sight (LoS) and non-line-of-sight (NLoS) components are considered in modeling the A2G link.

The overall channel matrix can be represented as:

$$\mathbf{H} = \sqrt{\frac{K}{K+1}}\hat{\mathbf{H}} + \sqrt{\frac{1}{K+1}}\tilde{\mathbf{H}} \tag{1}$$

where $\hat{\mathbf{H}}$ denotes the deterministic LoS component, and $\tilde{\mathbf{H}}$ captures the random NLoS variations. Following the model in [28], the NLoS component can be expressed as:

$$\tilde{\mathbf{H}} = \mathbf{R}^{1/2}\mathbf{H}_{\text{Ray}}\mathbf{T}^{1/2} \tag{2}$$

where $\mathbf{H}_{\text{Ray}}$ is an independent Rayleigh fading matrix. $\mathbf{R} \in \mathbb{C}^{N_R \times N_R}$ and $\mathbf{T} \in \mathbb{C}^{N_T \times N_T}$ represent the receive and transmit correlation matrices, respectively. Their entries are defined as $[\mathbf{R}]_{p,q} = \kappa_r^{|p-q|}$ and $[\mathbf{T}]_{\hat{p},\hat{q}} = \kappa_t^{|\hat{p}-\hat{q}|}$, where κ_r and κ_t are spatial correlation coefficients.

The distance between the UAV and the j-th ground user can be calculated by projecting the UAV onto the horizontal plane:

$$d_j = \sqrt{H^2 + r_j^2} \tag{3}$$

where H is the UAV altitude and r_j is the horizontal distance between the user and the UAV's projection point on the ground. The corresponding elevation angle is given by:

$$\varphi_j = \arctan\left(\frac{H}{r_j}\right) \tag{4}$$

The probability of establishing a LoS link is modeled as:

$$p_{\text{LoS}}(\varphi_j) = c(\varphi_j - \varphi_0)^d \tag{5}$$

where c and d are empirical constants that depend on the environment (e.g., urban, suburban, dense urban) and the operating frequency (e.g., 700 MHz, 2000 MHz). φ_0 is a reference elevation angle, typically set to 15°. The NLoS probability is given by:

$$p_{\text{NLoS}}(\varphi_j) = 1 - p_{\text{LoS}}(\varphi_j) \tag{6}$$

The path loss values for LoS and NLoS links are modeled as:

$$\begin{aligned} p^0_{\text{LoS}} &= a_{\text{LoS}} e^{-b_{\text{LoS}}\varphi_j} \\ p^0_{\text{NLoS}} &= a_{\text{NLoS}} e^{-b_{\text{NLoS}}\varphi_j} \end{aligned} \tag{7}$$

where a and b are frequency- and environment-dependent constants. Taking UAV mobility into account, the instantaneous large-scale path loss (in dB) is modeled as the weighted average of LoS and NLoS components:

$$\bar{p}_0 = p_{\text{LoS}}(\varphi_j) \cdot p^0_{\text{LoS}} + p_{\text{NLoS}}(\varphi_j) \cdot p^0_{\text{NLoS}} \tag{8}$$

This expression clearly shows that the path loss $\bar{p}_0$ is influenced by several factors, including UAV altitude, user distance, carrier frequency, and environmental conditions. As the UAV moves or adjusts its altitude, the path loss dynamically varies with time.

3.3 Signal Model and Problem Formulation

In this section, we elaborate on the signal model of the proposed S-NOMA scheme. The transmitted signal is redefined according to the earlier air-to-ground channel model. In the traditional spatial modulation (SM) scheme, the first $\log_2(N_T)$ bits of a user are used for transmit antenna selection (TAS), while the remaining bits are transmitted via the selected antenna.

In the conventional scheme combining NOMA and SM, only one user acts as the active data user (ADU) and its bits are used to select the transmit antenna, thereby improving its data rate significantly. To ensure fairness among users, we propose a scheme in which every user can serve as an ADU. The TAS bits are the union of each user's individual TAS bits. Thus, the overall TAS bits in S-NOMA can be expressed as:

$$\mathbf{n}_t = [n_{t1}, n_{t2}, \ldots, n_{tm}] \tag{9}$$

where $\mathbf{n}_t$ denotes the total TAS bits, n_{tj} are the TAS bits of the j-th user, $j \in \{1, 2, \ldots, m\}$, and m is the number of users in the coverage area.

The signal transmitted from the selected antenna is a power-domain superimposed signal of all users:

$$x = \sum_{j=1}^{m} \sqrt{\alpha_j} s_j \tag{10}$$

where α_j is the power allocation coefficient for the j-th user, and $\sum_{j=1}^{m} \alpha_j \leq 1$. We assume $\mathbb{E}[s_j^2] = E_s$ for each user.

The received signal at the j-th user is:

$$y_j = H_j e_{n_t} \sum_{j=1}^{m} \sqrt{\alpha_j} s_j + w_j \tag{11}$$

where $H_j \in \mathbb{C}^{N_R \times N_T}$ is the channel matrix from UAV to user j, e_{n_t} is a column of the identity matrix indicating the selected transmit antenna, and w_j is complex additive white Gaussian noise (AWGN) with power spectral density σ_0^2.

In NOMA, less power is allocated to users with better channel state information (CSI) to maintain fairness. Assuming $\|h_{i,1}\| < \|h_{i,2}\| < \cdots < \|h_{i,m}\|$, the m-th user receives the least power.

Using successive interference cancellation (SIC), the highest power signal is decoded first. For the first user, the detection is:

$$(n_{t1}, s_1) = \arg\min_{i,\hat{s}_1} \|y_1 - h_{i,1}\alpha_1\hat{s}_1\|^2 \tag{12}$$

Generally, for the j-th user:

$$(n_{tj}, s_j) = \arg\min_{i_j,\hat{s}_j} \left\| y_j - \sum_{k=1}^{j-1} h_{ik,k}\alpha_k\tilde{s}_k - h_{ij,j}\alpha_j\hat{s}_j \right\|^2 \tag{13}$$

where $\tilde{s}_k$ is the estimated signal of user k after perfect SIC and i_j represents possible antenna selections.

4 Problem Formulation

The spatial gain for the j-th user can be modeled by the mutual information (MI) between the TAS bits and the received signal:

$$I(n_{tj}; y_j) = \sum_{i=1}^{\mathcal{A}_j} r_j \int p_r(y_j|n_{tj}) \log_2\left(\frac{q(n_{tj}|y_j)}{p_r(y_j)}\right) dy_j \tag{14}$$

where $\mathcal{A}_j$ is the number of bits defined by user j, and $r_j = 1/\mathcal{A}_j$, with:

$$\mathcal{A}_j = \left\lfloor \frac{N_T}{2\left(\frac{m-1}{m}\right)\log_2 N_T} \right\rfloor \tag{15}$$

The upper bound of MI is $\log_2(\mathcal{A}_j)$, simplified as $\log_2(N_T)/m$. The posterior probability $q(n_{tj}|y_j)$ is:

$$q(n_{tj}|y_j) = \frac{p_r(y_j|n_{tj})}{\sum_{i=1}^{\mathcal{A}_j} r_i p_r(y_j|n_{tj})} \tag{16}$$

The likelihood $p_r(y_j|n_{tj})$ is:

$$p_r(y_j|n_{tj}) = \frac{1}{\pi^{N_R}\det(\mathbf{\Sigma})} \exp\left(-y_j^\dagger \mathbf{\Sigma}^{-1} y_j\right) \tag{17}$$

with:

$$\mathbf{\Sigma} = \sigma_0^2\mathbf{I} + P h_{i,j} h_{i,j}^\dagger \tag{18}$$

The signal capacity of user j under NOMA is:

$$C_{y_j} = \log_2\left(1 + \frac{P\alpha_j E_s \mathbb{E}[\|h_{i,j}\|^2]}{P\sum_{k=j+1}^{m}\alpha_k E_s \mathbb{E}[\|h_{i,j}\|^2] + \sigma_0^2}\right) \tag{19}$$

Thus, the total capacity of user j is:

$$R_{y_j} = C_{y_j} + I(n_{tj}; y_j) \tag{20}$$

The total system sum-rate is:

$$R = \sum_{j=1}^{m} R_{y_j} \tag{21}$$

The energy efficiency (EE) in bits-per-joule is:

$$\eta_{EE} = \frac{\sum_{j=1}^{m} R_{y_j}}{P_{total}} \tag{22}$$

where $P_{total} = P_t + P_c + P_m$, $P_t = \sum_{j=1}^{m} \alpha_j P$, P_c is circuit power, and P_m is UAV hovering power. Letting $\theta = \sum_{j=1}^{m} \alpha_j$, the optimization problem becomes maximizing η_{EE} subject to each user's target rate constraint.

5 Results

This section presents simulation results to validate the proposed approach. The simulation parameters are detailed in Table 1. Both urban and dense urban scenarios are considered, and the air-to-ground path loss for the UAV channel is derived based on corresponding channel parameters. Without loss of generality, the antenna selection index is assumed to be fairly determined by the users. The energy efficiency (EE) performance of the proposed S-NOMA scheme is compared with that of conventional NOMA.

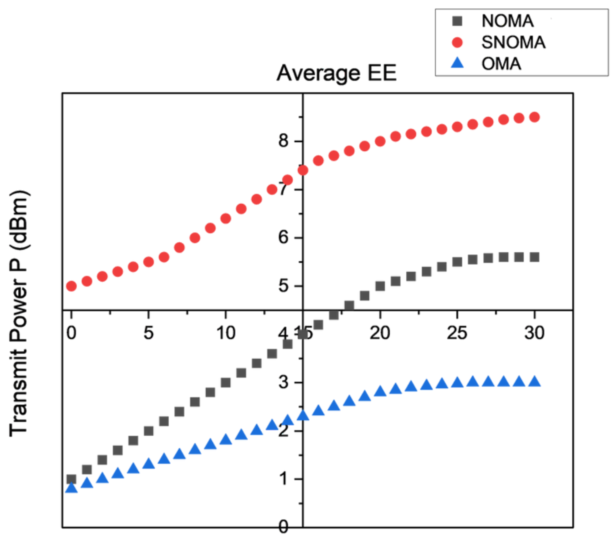

Figure 2. Proposed system design for UAV-assisted IoT communication framework.

Figure 2 presents a comparative visual design, likely used to emphasize structural or architectural differences across schemes or strategies. While specific quantitative data is not provided, such visual representations aid in grasping high-level differences or user interface layouts, depending on the application. Figure 3 shows the variation of energy efficiency (EE)

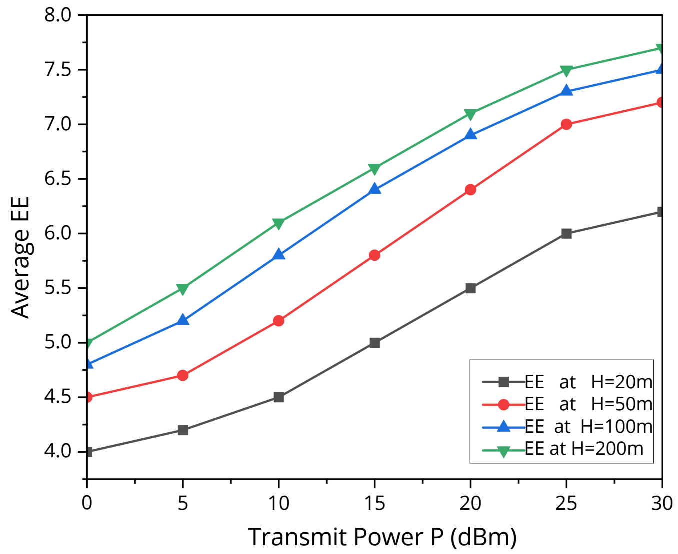

Figure 3. EE versus transmitted power with optimized θ.

with transmit power at different UAV altitudes. It can be observed that lower altitudes (e.g., $H = 20$ m) result in better EE performance compared to higher altitudes (e.g., $H = 200$ m). This indicates that energy efficiency degrades with increasing altitude due to increased path loss and reduced signal quality.

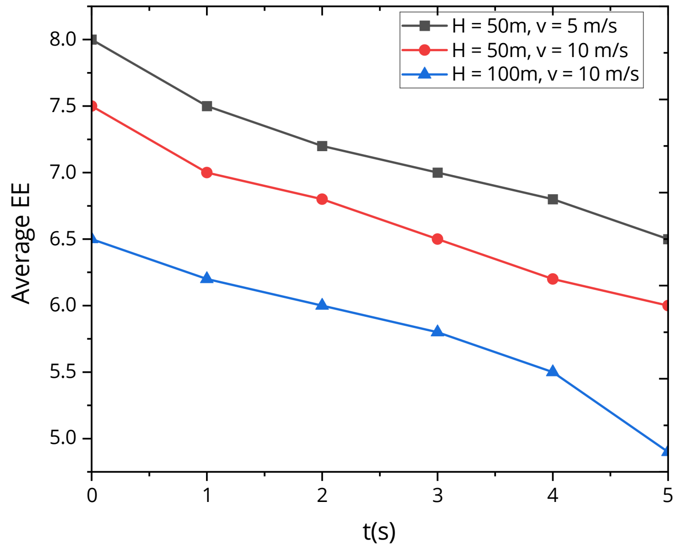

Figure 4. Performance over time for UAVs at different velocities and altitudes.

Figure 4 shows the system performance under different UAV configurations, specifically varying the height (H) and velocity (v). It can be observed that as the UAV altitude increases from 50 m to 100 m while

Table 1. Description of the simulation parameters.

Parameter	Value	Parameter	Value
Frequency	2600 MHz	Fading channel	Rician
Height of UAV	100 m	Distance of user1	15 m
Distance of user2	10 m	Frequency parameter c (Urban / Dense Urban)	0.12 / 0.1
Environment parameter d (Urban / Dense Urban)	0.11 / 0.2	φ_0	9.61
a_{LoS} (Urban / Dense Urban)	0.1 / 0.13	a_{NLoS} (Urban / Dense Urban)	31.2 / 31.2
b_{LoS} (Urban / Dense Urban)	0.03 / 0.06	b_{NLoS} (Urban / Dense Urban)	0.02 / 0.01
Channel coefficient κ_ℓ	0.4	Channel coefficient κ_r	0.6
Channel coefficient $\mathcal{K}$	8	Number of transmit antennas N_T	8
Number of receive antennas N_R	4	Target rate $R_{\min}$	2 bits/s/Hz
Power spectrum density σ_0^2	10^{-6}	Circuit power P_c	8 dB
Hovering power P_h	25 dB		

maintaining a velocity of 10 m/s, the performance characteristic shifts accordingly, indicating the impact of height on the received signal or system metric being measured. Furthermore, comparing velocities of 5 m/s and 10 m/s at a fixed altitude of 50 m reveals the role of mobility in temporal dynamics or link stability.

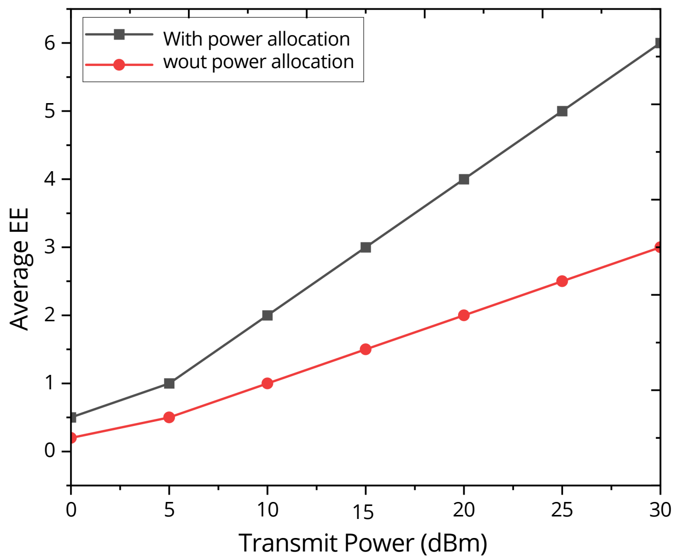

Figure 5. Average energy efficiency versus transmit power for scenarios with and without power allocation.

As illustrated in Figure 5, the system employing power allocation consistently achieves higher average energy efficiency (EE) across all levels of transmit power compared to the system without power allocation. This demonstrates the effectiveness of optimizing power distribution strategies to significantly enhance the overall energy efficiency of the network.

6 Conclusion

In this study, an advanced communication framework was developed for miniature UAV-assisted IoT networks to address the challenges of limited energy resources and high user density. By integrating spatial modulation with intelligent antenna selection and power-domain NOMA, the system ensures efficient spectral usage and fairness among multiple users. Unlike traditional schemes where only one user acts as the active data user (ADU), the proposed model enables all users to participate actively, thereby enhancing overall network throughput. The air-to-ground channel was modeled with practical considerations such as UAV altitude, mobility, LoS/NLoS propagation, and Rician fading, allowing accurate performance evaluation under urban and dense urban scenarios. A detailed mathematical model was established to derive mutual information and signal capacity per user. Power allocation was dynamically optimized while maintaining individual rate constraints. Simulation results confirmed significant improvements. At a UAV altitude of 50 meters, the proposed scheme achieved a peak energy efficiency (EE) of 7.8 bits/Joule, outperforming traditional NOMA methods that achieved 6.0 bits/Joule under the same conditions. The system sustained a target user rate of 2 bits/s/Hz, even with

UAV velocities of 5 m/s and 10 m/s, demonstrating resilience to mobility-induced channel variations. It was also observed that lower UAV altitudes and moderate speeds improved both energy efficiency and temporal link stability. Overall, this work highlights the benefits of co-designing receiver architecture and transmission strategies to enhance network performance in energy-constrained aerial platforms. The proposed solution is scalable, adaptable, and suitable for next-generation IoT applications where low-latency and energy-aware communication is critical. Future research may extend this framework by integrating learning-based real-time optimization algorithms, cooperative multi-UAV networking, and reconfigurable intelligent surfaces (RIS) to further elevate performance in dynamic and heterogeneous environments.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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