Cognitive Unmanned Aerial Vehicle-Aided Human Bond Communication System: Modeling and Performance Analysis

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\textbf{ABSTRACT} Effective networking over wireless media has become extremely essential today as communication between massive Internet of things (IoT) devices is on an increase, thereby leading to a limited spectrum resource for utilisation. Specifically, for healthcare infrastructure in a remote or critical situation, providing uninterrupted communication between the macro base station and IoT devices or user nodes is imperative. However, owing to their limited spectral capacity, unmanned aerial vehicles (UAVs)-based networks can provide an efficient solution and utilise both licensed and unlicensed bands for communication among users or devices. In this paper, our focus is on cache-enabled cognitive networking for secondary users (SUs) that accredits precise communication delivery for critical healthcare systems that are performed by the cognitive UAV (CUAV). In addition, we develop a caching strategy wherein a CUAV is capable of caching relevant information from high-power (HP) and moderate-power (MP) devices in its local and cloud storage by applying a non-orthogonal multiple-access method. In the downlink scenario, the CUAV proactively transmits the requested HP and MP information to the designated SUs considering this entire model over two states, namely effectual state and interference state, which we can realise by any presence or absence of interference. To maximise this system’s energy efficiency, we formulate an optimisation problem to minimise the transmission power and satisfy the target performance in terms of throughput for SUs. We solve the optimisation issue using the Lagrangian approach and the Karush-Kuhn-Tucker conditions. In all simulations, the energy efficiency during the effectual state renders an average performance of approximately 400% better than that of the interference state.

\textbf{INDEX TERMS} Caching, cognitive radio network, energy efficiency, human bond communication, non-orthogonal multiple access, optimisation, throughput, unmanned aerial vehicle.

\section{I. INTRODUCTION}
\subsection{A. BACKGROUND AND MOTIVATION}

Some of the key objectives of the potential universal communication environment are to enhance the standard of living by increasing convenience and enriching the experiences and circumstances of our daily activities. To realise this, several major technological advancements have centred on improving human interactions. The conventional approach to communication technology has always been to improve the information or signal so that the communication entities can manage them with the utmost efficiency. The limitation is that there is no transfer of information by such communication systems directly to the users’ awareness that will allow for a
more integrative sharing of sensory data. In relation to this, several articles have introduced the concept of human bond communication (HBC) to understand this dynamic growth that will prove to be a massive step toward achieving precise health applications, sensing, surgical operations, identifying emotions, collection of biological data for diagnosis purposes, remote contact with the human body, and neural communication [1], [2], [3].

Today, we need to understand the impacts of next-generation communication networks to incorporate the conceptualised idea of HBC systems and to create several high-end human sensory communication systems [4], [5]. The main motivation for developing HBC-compatible technology is to mitigate most of the complexities in healthcare diagnosis. For example, to efficiently monitor the impulsive nature and attention variation of a patient, an HBC-compatible system that can diagnose, process, and deliver all five-sense data for all-inclusive collaboration between the patient and the medical practitioner is an effective step toward modern diagnosis and treatment [2]. Similarly, with some specific modifications, this framework can also support patients with partial paralysis, blindness, disability, old age, and mental illness. To implement such a complex HBC network that precisely tracks and processes human sensory data for diagnostics, an extremely high energy efficiency and higher bandwidth communication is required, which a next-generation network technology scheme can deliver.

The benefits of utilising the HBC communication framework in the social and technical sectors are immense. Currently, multiple applications can adopt HBC principles such as cognitive therapies, wellness applications, disaster safety applications, and complex documentation [6]. Additionally, with regard to the radioactive effect on human health, in next-generation communication systems, signal waves transmitting at higher frequencies will attenuate considerably rapidly and will infiltrate the human body even less than the conventional lower-frequency systems [7]. This particular reason will also greatly benefit the development of a non-radioactive wearable HBC communication device, especially for medical patients. In [8] and [9], the importance of drones or unmanned aerial vehicle (UAV)-based systems, as well as the areas of drone deployment to facilitate drone-based first aid, basic product transportation system, blood sample delivery system, surveillance, and broadcasting information in a disaster-prone area, was highlighted. Even with the recent COVID-19 pandemic [10], [11], [12], drones can be useful for disinfectant spraying, distribution of medication and food for quarantined people, mobile temperature monitoring, and several other aerial assistance for field health personnel. When the HBC communication devices are remote from the macro base station (MBS), UAVs can assist. Due to their adaptability and mobility, UAV-assisted HBC systems have been used in cognitive radio (CR) environments to address the spectrum shortage issue in wireless communication.

**B. EXISTING RESEARCH WORKS**

Recently, the scientific community has demonstrated the opportunities and complexities of cognitive devices. UAV communication, and caching tools with a possible solution to alleviate most complexities introduced in some academic research. A comprehensive analysis of the extensive implementation of UAV systems in disaster control and health management applications is provided in [13] and [14], where the authors concentrated on ultrasonic sensing, neural networks, and geotagging to accurately classify the disaster-sensitive position, establish communication, and assist primary response by a network. In [15], a robust system architecture was presented to manage medical emergencies through a UAV-based network, where one UAV coordinates with another UAV based on its capabilities (i.e. existing power, signal strength, reliability), and undertakes necessary action to resolve the emergency.

The authors in [16] and [17] introduced a cognitive agent (CA) that executes mobile edge computing cognitive features in smart devices targeted at 5G mobile communication networks. Every smart computer that owns a CA can interpret intent, cache user information, contact data, and create activity profiles based on the user interface in the Internet of things (IoT) system. We see a related caching approach in [18], where the authors jointly suggest an edge caching technique that considers information awareness and a reward-based algorithm to encourage UAV-focused content sharing of the user equipment. Next, to realise the effectiveness of probabilistic caching, the authors in [19] investigated the service success probability in a heterogeneous network by implementing a base station (BS) in a UAV with different caching capacities and then maximising the probability caching placement. The practical implementation of any UAV-based communication is challenging owing to the endurance of the UAV; to mitigate this issue, the study of authors in [20] presented proactive caching as a viable solution. Additionally, in [20], the authors proposed a model in which the UAV caches data during the file caching process; subsequently, the ground user may recover the file and store the information in their local cache for every other ground user requiring similar material, thereby solving the endurance issue. A similar approach is presented in [21], where the authors demonstrated four major application scenarios of a UAV-supported ultra-dense network and then presented a power management framework based on network and spectrum state considerations.

The authors concentrated on a quality of experience system by integrating UAVs with caching functionality in small-cell networks to provide consumers with the most popular content from their local cache to mitigate backhaul congestion and then proposed a case study in network disturbance management in [22]. With similar intentions of increasing throughout, the authors of [23] provided a cache-enabled UAV model over an IoT machine-type device network by jointly optimising UAV deployment and formulating a concave problem for probabilistic caching placement. To guarantee the protection of UAV transmitted wireless networks, the
authors of [24] suggested a scheme under which a UAV with caching capacity must send data to any cache-enabled system during off-peak hours, and by adjusting the UAV’s trajectory and schedule, the security status of non-cached users can be preserved. In addition, the authors in [25] suggested a successful model, where they established a non-convex optimisation problem to optimise a cache-enabling UAV trajectory through a successive convex approximation dependent algorithm and the Dinkelbach method to achieve optimum energy efficiency.

With regard to the application of non-orthogonal multiple-access (NOMA)-based UAV architecture, the authors suggested fog-based computing and caching methods to release traffic burden from the network in [26], wherein they implemented a two-sided matching and swapping algorithm to optimise the energy efficiency for wireless UAV networks and to allocate power effectively; the authors developed a non-convex optimisation problem and then solved it through the difference of convex programming.

To alleviate the issue of spectrum scarcity, essential traffic, and content management, the authors of [27] suggested a cache-enabled UAV-BS for a cooperative CR network. The results from [27] illustrate the improved transmission efficiency between the UAV and the BS, as well as content management by allocating the licensed bandwidth for the secondary users (SUs) and direct transmission of cache-enabled UAVs to primary users (PUs). Moreover, to increase the data rate through UAV communication, the authors in [28] suggested a system for optimising efficient transmission by maximising the sensing range of the spectrum concerning the constraint of the PU intrusion throughput. According to [27] and [28], there are several limits. In [27], the issue of cache-enabled cognitive UAV (CUAV) networks has not been well addressed analytically or in terms of interference. As stated in [28], caching technology and NOMA scheme cannot be used in the CUAV network.

C. CONTRIBUTIONS AND ORGANISATION

Concerning the usage of CR application, in [27], the authors try to improve transmission capacity through CR by differentiating the communication channel used by the PUs and the SUs with the MBS and the UAV, respectively. Uniquely, in [28], the authors enhance the range of the cognitive sensing for the limit of any PU’s incursion throughput to optimise the efficient transmission. However, the aforementioned research [27], [28] neither observed nor formulated the energy efficiency and optimisation issues for a cache-enabled cognitive UAV (CUAV) network. In this paper, we investigate the performance related to the energy efficiency of a cache-enabled CUAV network as a possible solution to proper spectrum utilisation and interference management for HBC communication framework in a downlink scenario. In the following, we summarise the key contributions of our research.

• First, we propose a framework of cache-enabling cognitive network model that the CUAV caches from two high-power (HP) and moderate-power (MP) devices in the uplink scenario; it is then dispatched to serve the SUs with the requested data in the downlink scenario. In addition, we design a caching scheme concerning the requested data by the SUs. Further, we study a spectrum sensing scheme to identify idle channels and an interference temperature technique to protect primary communication (licensed communication) for the proposed model. Moreover, a power model and a channel model are provided for CUAV communication, applicable to both the uplink and downlink phases.

• Second, we derive the throughput and energy efficiency expressions in the downlink scenario regarding the requested information by SUs for effectual and interference states. In the considered network, a NOMA scheme is used for HP and MP device information.

• Third, we formulate an optimisation problem for the effectual and interference states, where we try to minimise the transmission power of CUAV and MBS while maintaining guaranteed throughput of HP and MP information. Subsequently, the formulated power-allocation problem is solved by utilising the decomposition method.

• Finally, we conduct simulations to evaluate the performance of the proposed NOMA scheme. By comparing the performance of the NOMA system with the corresponding orthogonal multiple access (OMA) system in the considered network, we show that the NOMA system outperforms its OMA system by achieving higher energy efficiency. In addition, we demonstrate that the proposed scheme outperforms the three benchmark schemes in simulation results.

The remainder of this paper is organised as follows. Section II covers the system model with a network, caching, spectrum sensing, and channel design. In Section III, we derive the expressions of throughput and energy efficiency. In Section IV, we solve the energy efficiency with the corresponding formulation of the optimisation problem. In Section V, we verify the effectiveness of our proposed system with energy efficiency and compare the results of the proposed system with benchmark schemes from the simulation. Finally, Section VI provides concluding statements and future work.

II. SYSTEM AND CHANNEL MODELS

A. NETWORK ARCHITECTURE

Consider a CUAV-enabled long-term-evolution communication system, in which carrier aggregates between licensed macro cells and unlicensed small cells [29]. As illustrated in Fig. 1, the macro cell is the primary cell with which PUs communicate and maintain their connection with the MBS. One small cell is the secondary cell comprising a CUAV (i.e. a small BS) connected to the SUs supporting an unlicensed carrier with MBS. A CUAV is connected to the MBS via a capacity-constrained backhaul link. Each PU is
connected to the MBS via a radio access link. In addition, each SU and cognitive IoT (CIoT) device are connected to the CUAV via a radio access link. In accordance with the network, CIoT devices transmit the sensing data to the CUAV in uplink, and CUAV dispatches to serve a group of SUs in the downlink. Each node is equipped with a single antenna and is capable of spectrum sensing. Assume that a CUAV is cache-enabled, has limited storage capacity, and hovered at a fixed position within a finite time \( T \) in three-dimensional (3D) space. Moreover, the MBS operates in 3D space with a fixed location, while the locations of all the SUs and the PUs are variable during the whole service time. The uplink and downlink transmissions make use of the same frequency channel but different time slots.

1) UPLINK PHASE
The uplink or sensing phase is referred to as the caching phase. In the uplink schema shown in Fig. 1, two types of CIoT devices are used: (i) High-power (HP\(^1\)) devices provide low latency, high reliability, and high-powered precise communication for patients requiring immediate (urgent) care and (ii) Moderate-power (MP) devices have moderate reliability and flexible latency with low-powered accurate communication that addresses conventional (non-urgent) responses to regular patients. As shown in Fig. 1, our network model comprises one CUAV with cache capacity, multiple HP devices, and multiple MP devices in the uplink phase. The set of HP and MP devices are denoted as \( N_h = \{1, 2, \ldots, N_h\} \) and \( N_m = \{1, 2, \ldots, N_m\} \), respectively, where \( N_h \) and \( N_m \) are the total number of HP and MP devices, respectively, under the CUAV coverage. Here, HP and MP devices transmit sensing data to the CUAV that will be subsequently forwarded to the MBS or SUs.

2) DOWNLINK PHASE
The downlink or serving phase is referred to as the delivery phase. After the completion of the sensing service, the CUAV\(^2\) dispatches to serve SUs with the cached data over the remote or critically located healthcare infrastructure, where CUAV acts as a secondary transmitter and SUs are secondary receivers. There are two types of SUs: SU-HP and SU-MP in which the SU-HP device downloads the HP data, and the SU-MP device downloads the MP data from the CUAV. Each SU-HP device was paired with another SU-MP device. The sets of SU-HPs and SU-MPs are denoted as \( N_{sh} = \{1, 2, \ldots, N_{sh}\} \) and \( N_{sm} = \{1, 2, \ldots, N_{sm}\} \), respectively, where \( N_{sh} \) and \( N_{sm} \) denote the total numbers of SU-HP and SU-MP devices, respectively. Therefore, SU is the sum of the SU-HP and SU-MP devices. The set of SUs is denoted by \( N_s = N_{sh} \cup N_{sm} \). The set of PUs is denoted by \( N_p = \{1, 2, \ldots, N_p\} \), where \( N_p \) is the total number of PUs. CUAV transmits the sensing data to SU-HP and SU-MP devices using the same subcarrier with different power levels because the NOMA technique is applied for the transmission of HP and MP data.

\(^1\)HP and MP devices are referred to as sensing transducers. The sensing transducers pick up all human sense data to make the subject more perceivable. The HP device receives the sensing data from the patient needing urgent attention that is then forwarded to the CUAV for caching. Similarly, the MP device obtains sensing information from patients needing regular care and later forward that sensing data to the CUAV for caching.

\(^2\)CUAV can directly deliver the sensing data to the SUs; otherwise, the CUAV requests the sensing data from the MBS and then transmits it to the requested SUs.
In the considered network, sensing data can be transmitted to the SU-HP and SU-MP devices via two types of links: (1) The sensing data are cached by CUAV (CUAV-SU-HP/SU-MP) and (2) The sensing data are cached by MBS and CUAV (MBS-CUAV-SU-HP/SU-MP). In the present study, the throughput is calculated according to MBS-CUAV-SU-HP/SU-MP.3

**B. CACHING SCHEME**

In such a network, the MBS with the cloud server has to store the sensing data (HP and MP data) owing to the limited caching capacity (i.e. caching size) of CUAV. If the sensing data requested by the SU-HP and SU-MP devices are cached at the CUAV, then the CUAV can directly deliver the sensing data to the SU-HP and SU-MP devices; otherwise, the CUAV requests the sensing data from the MBS and then transmits it to the requested SU-HP and SU-MP devices. Suppose that the MBS stores a total of \( S_d \) sensing data requested by all SU-HP and SU-MP devices, where the set of all data is denoted as \( S_d = \{1, 2, \ldots, S_d\} \), and the sizes of all data are equal. The CUAV can store maximum \( S_u \) data in its cache (generally, \( S_u < S_d \)). Thus, we denote \( \text{I}_d \) as the indexing factor denoting the completion status of any cached data and can be expressed as follows:

\[
\text{I}_d = \begin{cases} 
\Psi_{d,n}^{cu}, & \text{successful caching at CUAV} \\
1 - \Psi_{d,n}^{cu}, & \text{caching from MBS.}
\end{cases}
\]  

(1)

where \( \Psi_{d,n}^{cu} \) is the probability of requesting data served by CUAV. The probability of requesting data \( d \) by SU \( n \) is defined as \( \text{I}_d,n \) following the Zipf distribution [30]. Assume that SU \( n \) requests \( N_S \) sensing data from the sensing catalogue \( (S_u) \) at the CUAV and is defined as

\[
\Psi_{d,n}^{cu} = \frac{S_d^{1 - \delta} \ln N_S}{\sum_{i=1}^{S_d} i^{1 - \delta} \ln S_u},
\]  

(2)

where \( \delta \) is the skewness parameter \( (0 < \delta \leq 1) \). A similar proof for (2) is given in [31] when \( \delta = 1 \).

**C. SENSING AND PROTECTION OF PU**

Sensing the idle channels in the spectrum is a fundamental procedure for any cognitive system. Hence, all our secondary transmitters (HP, MP, and CUAV) in both the uplink and downlink phases will perform sensing operations to efficiently utilise idle channels to communicate with the receiver. Specifically, this sensing operation is essential for our research, and for efficient networking, we need to determine if there are any active local licensed transmitters (MBS) communicating with its receiver (PU). We realise this by comparing the signal-to-noise ratio (SNR) received from an MBS to a threshold SNR at CUAV/HP/MP. For instance, if the received SNR \( (\text{\theta}_{mb}) \) from the MBS is lower than the threshold SNR \( (\text{\theta}_{t}) \), which we set for the HP/MP/CUAV devices; then, we define a particular state as an *interface state*. Conversely, if the received SNR from the MBS is higher than the threshold SNR, we characterise that state as an *interference state*. Therefore, we identify \( \omega \) as a symbol of an effective and interference state. Additionally, \( \omega = 0 \) indicates that the MBS is inactive in communication with the receiver, causing no interference \( (\text{\theta}_{mb} < \text{\theta}_{t}) \) to active HP and MP signals. Conversely, we symbolise any interference \( (\text{\theta}_{mb} \geq \text{\theta}_{t}) \) to the HP and MP signals from the MBS as \( \omega = 1 \).

In the cognitive environment, PUs and SUs utilise the same carrier. Therefore, mutual interference can occur between PUs and SUs for the imperfect detection of idle channels. As CUAV may create harmful interference to PUs, CUAV transmission needs to be monitored and regulated. Hence, CUAV transmission is below a particular interference threshold \( (\text{I}_{th}) \) to defend the licensed PUs [33]. Mathematically, the average interference power constraint of the \( p \)th PU is defined as

\[
(P_{u,h} + P_{u,m}) |c_{u,p}|^2 \leq \text{I}_{th}, \quad \forall p \in N_p,
\]  

(4)

where \( P_{u,h} \) and \( P_{u,m} \) represent the transmitted power for the HP and MP signals from the CUAV, respectively. \( c_{u,p} \) represents the channel gain between CUAV and PU.

**D. CUAV POWER MODEL**

Without loss of generality, the CUAV hovers at a fixed location. Based on [11], [34], the minimum required power of the CUAV at the hover can be expressed as

\[
P_{hov} = \left[(m_{bo} + m_{ba} + m_{pa})g + F_{dr}\right]^{1.5} / \sqrt{0.5D_m^4 g_p D_m},
\]  

(5)

where \( m_{bo}, m_{ba}, \) and \( m_{pa} \) are the masses of the CUAV body, battery, and payload (in kg), respectively, \( g \) is the gravitational constant (in m/s2). \( F_{dr} \) is the total drag force and is defined as \( F_{dr} = 0.5 \rho_d v_d^2 (C_{ba}A_{ba} + C_{bd}A_{bd} + C_{pa}A_{pa}) \), where \( C_{ba}, \) \( C_{bd}, \) and \( C_{pa} \) are the drag coefficient of the CUAV body, battery, and payload, respectively; \( A_{bo}, A_{ba}, \) and \( A_{pa} \) are the projected area of the CUAV body, battery, and payload (in m2), respectively. \( \rho_d \) and \( v_d \) are the air density (in kg/m3) and the velocity in air (in m/s), respectively. \( n_r \) and \( D_m \) are the number of rotor and diameter (in m), respectively.

According to Eq. (5), the masses of the CUAV body and battery are related to hovering power, while the number of rotors is inversely proportional to hovering power. Except for mass and number of rotor, all other parameters are constant in the simplified analysis. The required mass-to-roter power ratio for octocopter and quadcopter is

\[
\frac{m_s}{m_{bo} + m_{ba}} = \left(\frac{m_{ba}}{m_{bo} + m_{ba}}\right)^{0.5} \times \left(\frac{n_r}{n_4}\right)^{0.5},
\]

where \( m_s = m_{bo} + m_{ba} \) is the masses of the CUAV body and battery for octocopter, \( m_4 = m_{bo} + m_{ba} \) is the masses

3The CUAV needs to first download the requested sensing data from the MBS and then transmits it to the requested SU-HP and SU-MP devices. Therefore the downlink transmission is comprised of two parts, the wireless backhaul links from the MBS to the CUAV and radio access links from the CUAV to the SU-HP and SU-MP devices.
of the CUAV body and battery for quadcopter, $n_b$ is the number of rotor for octocopter, and $n_d$ is the number of rotor for quadcopter, respectively. With $n_b = 8$ and $n_d = 4$, the required mass-to-rotor power ratio for an octocopter and quadcopter is $0.707 \times \left(\frac{m_b}{m_d}\right)^{1.5}$. However, the mass of the CUAV for an octocopter is more than that of a quadcopter. According to [34], the masses of the CUAV body and battery for octocopter and quadcopter are $m_b = 12$ kg and $m_d = 2$ kg, respectively. The required power ratio for octocopter and quadcopter is $0.707 \times 6 = 4.242$. As a result, the power consumption of an octocopter is approximately 4.25 times that of a quadcopter.

Therefore, the total CUAV power consumption is written as

$$P_{com} = P_t + P_c + P_d + P_{hov},$$

where $P_t$ is the uplink or downlink transmission power, $P_c$ and $P_d$ represent the operation power and spectrum sensing power, respectively, by the CUAV.

E. CHANNEL MODEL

In our system model, pathloss is identified as the attenuation of any signal quality propagating through the space between the transmitters and the receivers. Specifically, we presume that all channel gains are independent and that all channel state information is accessible at the time of transmission. Thereafter, we consider the pathloss and fast fading effects within the channel gains equation as [35]:

$$c_{ab} = \frac{\tilde{c}_{ab}}{\sqrt{PL_{ab}^\text{LoS}/PL_{ab}^\text{NLoS}}},$$

where $c_{ab}$ represents the channel gain between any two nodes $a$ and $b$. Next, $PL$ denotes the pathloss between $a$ and $b$ over the distance $d_{ab}$ and can be expressed as,

$$d_{ab} = \sqrt{(a_i - b_i)^2 + (a_j - b_j)^2 + (a_k - b_k)^2},$$

where $a_i$ and $b_i$ are the height of two nodes $a$ and $b$. We use the subscript $a$, $b$, $c$, $d$ to denote CUAV, MBS, outdoor, and indoor, respectively. Similarly, from [35], we can signify a fast fading channel gain ($\tilde{c}_{ab}$) between nodes $a$ and $b$ as follows:

$$\tilde{c}_{ab} = \sqrt{\frac{K}{1 + K}} \tilde{c}_{\text{LoS}} + \sqrt{\frac{1}{1 + K}} \tilde{c}_{\text{NLoS}},$$

where $K$ denotes the Rician K-factor. $\tilde{c}_{\text{LoS}}$ denotes the line-of-sight (LoS) channel with $|\tilde{c}_{\text{LoS}}| = 1$. $\tilde{c}_{\text{NLoS}}$ is an arbitrarily scattered non-LoS (NLoS), representing a random variable with zero mean and unit variance. Specifically, we considered four types of communication model channels (e.g. CUAV-to-MBS/PU, CUAV-to-SU, MBS-to-PU, and MBS-to-SU) for our system model analysis.

1) CUAV-TO-MBS/PU COMMUNICATION

The CUAV-to-MBS/PU channel consists of both fading (LoS) and non-fading (NLoS) elements. Thereafter, we can compute the pathloss probability ($\zeta^o$) for outdoor environment considering the hovering of the CUAV as [32], [35]:

$$\zeta^o = \begin{cases} 
\frac{1}{1 + \psi \exp(-\varrho(\theta - \psi))} & \text{LoS link}, \\
\frac{1}{1 + \psi \exp(-\varrho(\theta - \psi))} & \text{NLoS link}, 
\end{cases}$$

where $\psi$ and $\varrho$ denote the environmental constants for the LoS and NLoS links, respectively. Moreover, $\theta$ represents the angle of elevation \((\theta = \tan^{-1}\left(\frac{|h_a - h_b|}{\sqrt{(a_i - b_i)^2 + (a_j - b_j)^2}}\right))\) between the $a$ and $b$ nodes. Hence, the CUAV-to-MBS/PU pathloss ($P^o$) for both LoS and NLoS links in decibels (dB) can be written as [35]:

$$P^o(d_{ab}) = \begin{cases} 
10\rho \log_{10} \left(\frac{4\pi d_{ab}}{\lambda}\right) + \alpha_{\text{LoS}} & \text{LoS link}, \\
10\rho \log_{10} \left(\frac{4\pi d_{ab}}{\lambda}\right) + \alpha_{\text{NLoS}} & \text{NLoS link}, 
\end{cases}$$

where $\lambda = \frac{\tilde{c}_{fa}}{f_{ca}}$, $\rho$ is the pathloss exponent, $\lambda$ is the wavelength, $f_{ca}$ is the carrier frequency, and $c$ is the speed of light. Moreover, $\alpha_{\text{LoS}}$ and $\alpha_{\text{NLoS}}$ are the factors of attenuation due to the LoS and NLoS channels, respectively. The mean pathloss of outdoor environment considering the probabilities for both LoS and NLoS is computed as follows:

$$PL^o_{\text{LoS}}(d_{ab}) = \zeta^o_{\text{LoS}} P^o_{\text{LoS}} + \zeta^o_{\text{NLoS}} P^o_{\text{NLoS}}.$$  \hspace{1cm} (11)

2) CUAV-TO-SU COMMUNICATION

The pathloss for outdoor-to-indoor environment is computed as follows [36]:

$$PL^i_{\text{LoS}}(d_{ab}) = PL^o_{\text{LoS}}(d_{ax}) + \alpha_{\text{wall}} d_{sb} + n_{\text{wall}} L_{\text{wall}},$$

where $PL^o_{\text{LoS}}(d_{ax})$ denotes the pathloss between $a$ and external wall of building ($x$) over the distance $d_{ax}$. $d_{sb}$ is the distance between $x$ and $b$. $PL^i_{\text{LoS}}(d_{ax})$ is calculated using Eq. (11). $\alpha_{\text{wall}}$ is the internal wall attenuation factor (in dB/m), $n_{\text{wall}}$ is the total number of penetrated internal walls, and $L_{\text{wall}}$ is the internal wall attenuation loss (in dB).

3) MBS-TO-PU COMMUNICATION

For this scenario, we consider that the MBS-to-PU channel comprises a NLoS element. Hence, the pathloss expression for outdoor environment is as follows [37]:

$$PL^o_{\text{LoS}}(d_{ab}) = 161.56 - (24.37 - 3.7(20/h_a^2)) \log_{10}(h_a) + (43.42 - 3.1 \log_{10}(h_a)) \log_{10}(d_{ab}) - 3) + 20 \log_{10}(f_{ca}) - (3.2(\log_{10}(11.75 h_b)^2) - 4.97).$$  \hspace{1cm} (13)

4) MBS-TO-SU COMMUNICATION

Similar to Eq. (12), the pathloss of MBS-to-SU channel for outdoor-to-indoor environment is computed as follows [36]:

$$PL^i_{\text{LoS}}(d_{ab}) = PL^o_{\text{LoS}}(d_{ax}) + \alpha_{\text{wall}} d_{sb} + n_{\text{wall}} L_{\text{wall}}.$$  \hspace{1cm} (14)

where $PL^o_{\text{LoS}}(d_{ax})$ is calculated using Eq. (13).
III. PERFORMANCE ANALYSIS

In this section, we analyse the performance metrics such as the throughput (data rate) and corresponding energy efficiency in the downlink environment.

A. THROUGHPUT

1) EFFECTIVE THROUGHPUT ($\omega = 0$)

We identify throughputs for HP and MP signals as effective when there is no interference from any licensed device, implying that MBS does not actively communicate in the downlink scenario. Power-domain NOMA serves the two SU simultaneously and applies successive interference cancellation (SIC) at the CUA, MBS, and SU equipment for signal separation. A natural SIC strategy is to first decode the HP signal and then decode the MP signal if the HP signal can be decoded and removed successfully. Thus, considering $\omega = 0$, we can derive an expression for the effective throughput of the $n$th SU-HP ($\forall n \in \mathbb{N}_s$) as follows:

$$ET_{hn}^{0} = \Psi_{d,n}^{cu}te_{u,hn}^{0} + (1 - \Psi_{d,n}^{cu}) \frac{t_cT_{u,hn}^{0}T_{m,hn}^{0}}{t_cT_{u,hn}^{0}T_{m,hn}^{0} + t_cT_{u,hn}^{0}}$$

(15a)

$$T_{u,hn}^{0} = B \log_2 \left( 1 + \frac{P_{u,hn} |c_{u,hn}|^2}{\sigma^2 + P_{u,mn} |c_{u,mn}|^2} \right).$$

(15b)

$$T_{m,hn}^{0} = B \log_2 \left( 1 + \frac{P_{m,hn} |c_{m,hn}|^2}{\sigma^2 + P_{m,mn} |c_{m,mn}|^2} \right).$$

(15c)

where $t_c = \frac{\lambda_{c,n}}{\lambda_{s,n}}$, $\rho_p (\omega = 0) (1 - \rho_{fa})$, $t_1$ and $t_2$ denote the transmission and sensing times, respectively. $B$ represents the system bandwidth. $P_{u,hn} + P_{u,mn} \leq P_{t,u}$, where $P_{t,u}$ represents the total power budget of the CUA, $P_{m,hn} + P_{m,mn} \leq P_{t,m}$, where $P_{t,m}$ represents the total power budget of the MBS. For any $n$ element in $\mathbb{N}_s$, $T_{u,hn}$ denotes the throughput between the CUA and SU-HP devices, and $T_{m,hn}$ denotes the throughput between SU-HP and CUAV for the HP signal. $P_{u,hn}$ and $P_{u,mn}$ represent the transmitted power of the HP and MP signals from the CUA. $P_{m,hn}$ and $P_{m,mn}$ represent the transmitted power of the HP and MP signals from the MBS. Moreover, the channel gain between the CUA and SU-HP devices is denoted by $c_{u,hn}$, and the channel gain between the MBS and CUAV for the HP signal is denoted as $c_{m,hn}$.

$\sigma^2$ denotes noise power. In addition, we introduce a probability function in (3) as $\rho_p (\omega = 0)$, which is valid for the inactive transmission state of the MBS. In our throughput expression, $\rho_{fa}$ is the resultant probability that exceeds a certain threshold value when only noise is present (i.e. no realisable signal) at the time of sensing operation for the MBS, which is also known as an alarm of false detection. Hereafter, we represent the entire term, $\rho_p (\omega = 0) (1 - \rho_{fa})$ as a detection probability owing to an interference-free channel from any MBS.

Similarly, we derive the effective throughput of the $n$th SU-HP ($\forall n \in \mathbb{N}_s$) when the MBS is inactive on transmission as follows:

$$ET_{mn}^{0} = \Psi_{d,m}^{cu}te_{u,mn}^{0} + (1 - \Psi_{d,m}^{cu}) \frac{t_cT_{u,mn}^{0}T_{m,mn}^{0}}{t_cT_{u,mn}^{0}T_{m,mn}^{0} + t_cT_{u,mn}^{0}}$$

(16a)

$$T_{u,mn}^{0} = B \log_2 \left( 1 + \frac{P_{u,mn} |c_{u,mn}|^2}{\sigma^2 + \Theta P_{u,mn} |c_{u,mn}|^2} \right).$$

(16b)

$$T_{m,mn}^{0} = B \log_2 \left( 1 + \frac{P_{m,mn} |c_{m,mn}|^2}{\sigma^2 + \Theta P_{m,mn} |c_{m,mn}|^2} \right).$$

(16c)

where $T_{u,mn}$ denotes the throughput between the CUAV and SU-MP devices, and $T_{m,mn}$ denotes the throughput between MBS and CUAV for the MP signal. The channel gain between CUAV and SU-MP is denoted as $c_{u,mn}$, and the channel gain between CUAV and MBS for the MP signal is denoted as $c_{m,mn}$. $\Theta$ represents the SIC coefficient, which varies between 0 and 1. $\Theta = 0$ implies perfect SIC, and $\Theta = 1$ implies imperfect SIC.

2) INTERFERENCE THROUGHPUT ($\omega = 1$)

Alternatively, in this case, if the MBS is active in communication alongside CUAV, we recognise the throughput as an interference throughput. Hence, we can develop the interference throughput of the $n$th SU-HP ($\forall n \in \mathbb{N}_s$) as follows:

$$ET_{hn}^{1} = \Psi_{d,n}^{cu}T_{u,hn}^{1} + (1 - \Psi_{d,n}^{cu}) \frac{t_tT_{u,hn}^{1}T_{u,hn}^{1}}{t_tT_{u,hn}^{1}T_{u,hn}^{1} + t_tT_{u,hn}^{1}}$$

(17a)

$$T_{u,hn}^{1} = B \log_2 \left( 1 + \frac{P_{u,hn} |c_{u,hn}|^2}{\sigma^2 + I_{umn}} \right).$$

(17b)

$$T_{m,hn}^{1} = B \log_2 \left( 1 + \frac{P_{m,hn} |c_{m,hn}|^2}{\sigma^2 + P_{m,mn} |c_{m,mn}|^2} \right).$$

(17c)

where $t_t = \frac{\lambda_{t,n}}{\lambda_{s,n}}$, $\rho_p (\omega = 1) (1 - \rho_{de})$, $I_{umn} = P_{u,mn} |c_{u,mn}|^2 + P_{mn} |c_{m,mn}|^2$, $P_{umn} = P_{m,hn} + P_{m,mn}$, $P_{mn}$ represents the transmission power of the MBS, and $c_{m,mn}$ represents the channel gain from the MBS to SU-HP. For the probability function, $\rho_p (\omega = 1)$ symbolises the active state of the MBS communication. Distinctively, in (3), $\rho_{de}$ signifies the probability of detecting a target signal when the resultant probability is greater than a particular threshold value, implying that noise is present in the system. Hence, the entire term $\rho_p (\omega = 1) (1 - \rho_{de})$ is an inadequate probability of detection for any SUs that face interference from the MBS.

Similarly, the interference throughput of the $n$th SU-MP ($\forall n \in \mathbb{N}_s$) can be derived as follows:

$$ET_{mn}^{1} = \Psi_{d,m}^{cu}T_{u,mn}^{1} + (1 - \Psi_{d,m}^{cu}) \frac{t_tT_{u,mn}^{1}T_{m,mn}^{1}}{t_tT_{u,mn}^{1}T_{m,mn}^{1} + t_tT_{u,mn}^{1}}$$

(18a)

$$T_{u,mn}^{1} = B \log_2 \left( 1 + \frac{P_{u,mn} |c_{u,mn}|^2}{\sigma^2 + I_{umn}} \right).$$

(18b)
\[ T_{mn}^1 = B \log_2 \left( 1 + \frac{P_{mn} |c_{mn}|^2}{\sigma^2 + \Theta P_{mn,ln} |c_{mn}|^2} \right), \]  

where \( I_{ln} = \Theta P_{ln,hu} |c_{lu}|^2 + P_{ln} |c_{ln}|^2 \). \( c_{mn} \) represents the channel gain from the MBS to SU-MP.

**B. ENERGY EFFICIENCY \((\alpha = 0, 1)\)**

In our research, we establish the energy efficiency for our system architecture as the ratio of the throughput for HP and MP signals to the total power utilisation by the CUAV and MBS. Thus, we can derive the energy efficiency of the nth SU (\( \forall n \in N \)) by considering the effective state as follows:

\[ \xi_n^0 = \frac{\mathcal{E}T_{ln}^0 + \mathcal{E}T_{mn}^0}{P_{ln,hu} + P_{ln,nu} + P_{mn} + P_{mn,ln} + P_{const}}. \]  

where \( P_{const} = P_e + P_s + P_{hop} \). Using a similar approach, we can develop the energy efficiency of the nth SU (\( \forall n \in N \)) by considering the interference state as follows:

\[ \xi_n^1 = \frac{\mathcal{E}T_{ln}^1 + \mathcal{E}T_{mn}^1}{P_{ln,hu} + P_{ln,nu} + P_{mn} + P_{mn,ln} + P_{const}}. \]  

**IV. OPTIMISATION PROBLEM FORMULATION AND SOLUTION**

In this section, we formulate the optimisation problem of energy efficiency for the effectual and interference cases. Subsequently, by developing an optimisation problem, we obtain optimal solutions for our system.

**A. EFFECTUAL ENERGY EFFICIENCY OPTIMISATION**

As mentioned in (19), a high energy efficiency can be obtained by finding the optimal transmit power of the MBS and CUAV with the maximised effective throughput of the HP and MP signals. Therefore, single-objective optimisation problem (SOP) at the nth SU (\( \forall n \in N \)) can be formulated as follows:

\[ \min_{P_{ln,hu}, P_{ln,nu}, P_{mn,ln}, P_{mn,nu}} P_{ln,hu} + P_{ln,nu} + P_{mn} + P_{mn,ln} \]  

s.t. \( \Psi_{d,n}^{\rho_0} T_{ln,hu}^0 \geq T_{ln,hu}^0 \), \( 1 - \Psi_{d,n}^{\rho_0} T_{ln,nu}^0 \geq T_{ln,nu}^0 \), \( 1 - \Psi_{d,n}^{\rho_0} T_{mn,ln}^0 \geq T_{mn,ln}^0 \), \( 1 - \Psi_{d,n}^{\rho_0} T_{mn,nu}^0 \geq T_{mn,nu}^0 \), \( P_{ln,hu} + P_{ln,nu} \leq P_{ln,hu} \), \( P_{mn} + P_{mn,ln} \leq P_{mn} \), \( P_{ln,hu} \leq P_{ln,hu} \), \( P_{mn} \leq P_{mn} \), \( P_{mn,ln} \leq P_{mn,ln} \) \( (21a) \) \( (21b) \) \( (21c) \) \( (21d) \) \( (21e) \) \( (21f) \) \( (21g) \) \( (21h) \) \( (21i) \) \( (21j) \)

where \( T_{ln,hu}^0, T_{ln,nu}^0, T_{mn,ln}^0, T_{mn,nu}^0 \), and \( T_{mn,ln}^0, T_{mn,nu}^0 \) represent the intended effectual throughput between CUAV and SU-HP, between CUAV and MBS for HP signal, between CUAV and SU-MP, and between CUAV and MBS for MP signal. From (21), the objective function (21a) is the sum of the power transmitted by CUAV and MBS. In (21a), the transmit power of the CUAV satisfies the constraints (21b), (21d), (21f), (21g), and (21i). Similarly, the transmit power of the MBS is satisfied by the constraints (21c), (21e), (21h), and (21j). According to [38], the optimisation problem (21) is solved by decomposing the problem into two sub-problems: (i) MBS power allocation and (ii) CUAV power allocation. Finally, we propose a transmit power allocation (TPA) algorithm based on the solution of the two sub-problems, as given in Algorithm TPA 1.

1) **MBS POWER ALLOCATION**

According to (21), the aim of this suboptimisation is to determine the minimum transmit power of MBS with the maximised effectual throughput of HP and MP signals. Thus, the suboptimisation problem can be reformulated as follows:

\[ \min_{P_{mn,ln}, P_{mn,nu}} P_{mn,ln} + P_{mn,nu} \]  

s.t. \( \psi_{2,nu}^{\rho_0} T_{mn,ln}^0 \geq T_{mn,ln}^0 \), \( \psi_{2,nu}^{\rho_0} T_{mn,nu}^0 \geq T_{mn,nu}^0 \), \( P_{mn} + P_{mn,ln} \leq P_{mn} \), \( P_{mn} \leq P_{mn} \), \( (22a) \) \( (22b) \) \( (22c) \) \( (22d) \) \( (22e) \)

where the objection function (22a), constraints (22d), and (22e) are linear functions with respect to the two positive parameters \( P_{mn,ln} \) and \( P_{mn,nu} \). Constraints (22b) and (22c) are non-convex functions. Thus, this subproblem is a non-convex problem. A detailed proof is provided in Appendix A. Now, we modify the constraints (22b) and (22c) and then find the subproblem (22) as follows:

\[ \min_{P_{mn,ln}, P_{mn,nu}} P_{mn,ln} + P_{mn,nu} \]  

s.t. \( \psi_{2,nu}^{\rho_0} T_{mn,ln}^0 \geq T_{mn,ln}^0 \), \( \psi_{2,nu}^{\rho_0} T_{mn,nu}^0 \geq T_{mn,nu}^0 \), \( P_{mn} + P_{mn,ln} \leq P_{mn} \), \( P_{mn} \leq P_{mn} \), \( (22d) \) \( (22e) \)

(23a) \( (23b) \) \( (23c) \)

where \( \psi_1 = 1/(2(1 - \frac{T_{mn,ln}^{\rho_0}}{\lambda - 1}) - 1) \) and \( \psi_2 = 1/(2(1 - \frac{T_{mn,nu}^{\rho_0}}{\lambda - 1}) - 1) \). Subproblem (23) is a linear optimisation problem. The optimal solutions are provided in Theorem 1.

**Theorem 1:** The optimal power allocations of MBS to problem (23) for HP and MP signals in effectual case can be expressed as

\[ P_{lm,ln}^{\ast} = \max \left( P_{lm,ln}^{\ast}, P_{lm,nu}^{\ast} \right) \]  

\[ P_{lm,nu}^{\ast} = \min \left( P_{lm,ln}^{\ast}, P_{lm,nu}^{\ast} \right) \]  

where \( P_{lm,ln}^{\ast} = \frac{P_{lm} |c_{lu}|^2 + \sigma^2}{1 + (1 + \psi_1) |c_{lu}|^2}, \) \( P_{lm,nu}^{\ast} = \frac{\psi_1 P_{lm} |c_{lu}|^2 + \sigma^2}{(1 + (1 + \psi_1) |c_{lu}|^2)}, \) \( P_{lm,ln}^{\ast} = \frac{\psi_2 P_{lm} |c_{ln}|^2 + \sigma^2}{(1 + (1 + \psi_1) |c_{ln}|^2)}, \) and \( P_{lm,nu}^{\ast} = \frac{\psi_2 P_{lm} |c_{ln}|^2 + \sigma^2}{(1 + (1 + \psi_1) |c_{ln}|^2)} \).

**Proof:** The proof of the Theorem 1 is referred to the Appendix B.
2) CUAV POWER ALLOCATION

Based on (21), we obtain the minimum transmission power of CUAV within a range of $P_{t,u}$. Thus, we can reformulate the suboptimisation problem as follows:

$$\begin{align}
\min_{P_{u,hn},P_{u,mm}} & P_{u,hn} + P_{u,mm} \\
\text{s.t.} & \Psi_d^u P_{u,hn} T_{u,hn}^0 \geq T_{u,hc}^0, \\
& \Psi_d^u P_{u,mm} T_{u,mm} \geq T_{u,mc}, \\
& (P_{u,hn} + P_{u,mm}) |c_{u,p}|^2 \leq I_{th}, \quad \forall p \in N_p, \\
& P_{u,hn} + P_{u,mm} \leq P_{t,u}, \\
& P_{u,mm} \leq P_{u,hn},
\end{align}$$

(24a)

(24b)

(24c)

(24d)

(24e)

Here, the objective function (24a) with constraints (24d), (24e), and (24f) are all linear functions for two positive parameters (i.e. $P_{u,hn}$ and $P_{u,mm}$). Next, the constraints (24b) and (24c) are both non-convex functions, which makes this subproblem non-convex. The proof is similar to that in Appendix A. Hence, after modifying the constraints (24b) and (24c), the subproblem (24) can be obtained as follows:

$$\begin{align}
\min_{P_{u,hn},P_{u,mm}} & P_{u,hn} + P_{u,mm} \\
\text{s.t.} & P_{u,hn} |c_{u,mm}|^2 + \sigma^2 - \nu_3 P_{u,hn} |c_{u,mm}|^2 \leq 0, \\
& \Theta P_{u,hn} |c_{u,mm}|^2 + \sigma^2 - \nu_4 P_{u,mm} |c_{u,mm}|^2 \leq 0, \\
& \text{(24d), (24e), & (24f)}, \quad (25d)
\end{align}$$

(25a)

(25b)

(25c)

(25d)

where $\nu_3 = 1/(2^d - 1)$ and $\nu_4 = 1/(2^d - 1)$.

Subproblem (25) can be seen as a linear optimisation problem and the optimal solutions are provided in Theorem 2.

**Theorem 2: The optimal power allocations of CUAV to problem (25) for HP and MP signals in effectual case can be expressed as**

$$\begin{align}
P^*_m = \min \left( P_{u,hn}^{12}, P_{u,mm}^{34} \right), \\
P^*_m = \min \left( P_{u,mm}^{12}, P_{u,mm}^{34} \right),
\end{align}$$

(26a)

(26b)

(26c)

(26d)

where $P_{u,hn}^{12} = \max \left( P_{u,hn}^{12}, P_{u,mm}^{34} \right)$, $P_{u,mm}^{34} = \max \left( P_{u,hn}^{12}, P_{u,mm}^{34} \right)$.

**Proof:** The proof of the Theorem 2 is referred to the Appendix C.

Based on the suboptimisation problem (23) and (25), the final procedure is stated in algorithm TPA 1 below:

TPA 1: Transmit Power Allocation Algorithm for Effectual Case

1. **Input:** Initial parameters given in Table 1;
2. for all $n \in \mathcal{N}_f$ do
3. Decompose the problem (21) into (23) and (25);
4. Compute the optimal solutions such as $P^*_m$ and $P^*_m$ based on Theorem 1;
5. Compute the optimal solutions such as $P^*_m$ and $P^*_m$ based on Theorem 2;
6. $\xi_n^0 \leftarrow P^*_m, P^*_m, P^*_m, P^*_m$;
7. end for
8. **Output:** $\xi_n^0(P^*_m, P^*_m, P^*_m, P^*_m)$ for $\forall n \in \mathcal{N}_f$.

B. INTERFERENCE ENERGY EFFICIENCY OPTIMISATION

As mentioned in (20), we formulate the optimisation problem for the interference energy efficiency when the MBS is active. Here, we attempt to maximise the throughput of the HP and MP signals while maintaining the collective transmission power of the HP and MP signals less than $P_{t,u}$ and $P_{t,u}$. Hence, we can express the SOP at the nth SU ($\forall n \in \mathcal{N}_f$) as

$$\begin{align}
\min_{P_{u,hn},P_{u,mm}} & P_{u,hn} + P_{u,mm} + P_{m,hn} + P_{m,mm} \\
\text{s.t.} & \Psi_d^u T_{u,hn} \geq T_{u,mc}, \\
& (1 - \Psi_d^u) T_{m,hn} \geq T_{m,mc}, \\
& (1 - \Psi_d^u) T_{m,mm} \geq T_{m,mc}, \\
& (P_{u,hn} + P_{u,mm}) |c_{u,p}|^2 \leq I_{th}, \forall p \in \mathcal{N}_p, \\
& P_{u,hn} + P_{u,mm} \leq P_{t,u}, \\
& P_{m,hn} + P_{m,mm} \leq P_{t,m}, \\
& P_{m,mm} \leq P_{u,hn}, \\
& P_{m,mm} \leq P_{u,hn},
\end{align}$$

(26a)

(26b)

(26c)

(26d)

(26e)

(26f)

where $T_{u,mc}, T_{m,mc}$ and $T_{m,mc}$ signify the intended interference throughputs between the nodes CUAV and SU-HP, CUAV and MBS for the HP signal, CUAV and SU-MP, and CUAV and MBS for the MP signal. The objective function (26a) is a collective sum of the power transmitted by both the CUAV and the MBS. In addition, the transmission power of the CUAV in (26a) is satisfied by the constraints (26b), (26d), (26f), (26g), and (26i). Equivalently, MBS transmit power is satisfied with (26c), (26e), (26h), and (26i), and similarly with the effectual state, the entire problem (26) has been decomposed into two sub-problems namely: (i) MBS power allocation and (ii) CUAV power allocation. Finally, we propose a TPA algorithm owing to the solution of two sub-problems, as given in Algorithm TPA 2.
1) MBS POWER ALLOCATION

According to (26), the aim of this suboptimisation is to determine the minimum transmit power of MBS with the maximised throughput of HP and MP signals. Thus, the suboptimisation problem can be reformulated as follows:

\[
\begin{align*}
\min_{P_{m,hn}, P_{m,mn}} & \quad P_{m,hn} + P_{m,mn} \\
\text{s.t.} \quad & \quad (1 - \Psi_{d,a}^{A}) T_{m,hc}^{1} \geq T_{m,hc}^{1}, \\
& \quad (1 - \Psi_{d,a}^{A}) T_{m,mn}^{1} \geq T_{m,mn}^{1}, \\
& \quad P_{m,hn} + P_{m,mn} \leq P_{t,m}, \\
& \quad P_{m,mn} \leq P_{m,mn}.
\end{align*}
\]  
\[
(27a)
\]
\[
(27b)
\]
\[
(27c)
\]
\[
(27d)
\]
\[
(27e)
\]

where the objection function (27a), constraints (27d), and (27e) are linear functions with respect to the two positive parameters \(P_{m,hn}\) and \(P_{m,mn}\). Constraints (27b) and (27c) are non-convex functions. Thus, this subproblem is non-convex problem. A similar proof is provided in Appendix A. Now, we modify the constraints (27b) and (27c) and then find the subproblem (27) as follows:

\[
\begin{align*}
\min_{P_{m,hn}, P_{m,mn}} & \quad P_{m,hn} + P_{m,mn} \\
\text{s.t.} \quad & \quad P_{m,mn} |c_{m,hn}|^2 + \sigma^2 - \upsilon_5 P_{m,hn} |c_{m,hn}|^2 \leq 0, \\
& \quad \Theta P_{m,hn} |c_{m,mn}|^2 + \sigma^2 - \upsilon_6 P_{m,mn} |c_{m,mn}|^2 \leq 0, \\
& \quad (27d) \ & \ & \text{&} \ \ (27e),
\end{align*}
\]  
\[
(28a)
\]
\[
(28b)
\]
\[
(28c)
\]
\[
(28d)
\]

where \(\upsilon_5 = 1/(2(1-\Psi_{d,a}^{A})^B - 1)\) and \(\upsilon_6 = 1/(2(1-\Psi_{d,a}^{A})^B - 1)\). Subproblem (28) is a linear optimisation problem that can be given in Theorem 3.

Theorem 3: The optimal power allocations of MBS to problem (28) for HP and MP signals in interference case can be expressed as

\[
\begin{align*}
P^*_u,hn & = \max \left( p^3_{m,hn}, P^4_{m,hn} \right), \\
P^*_u,mn & = \min \left( p^3_{m,hn}, P^4_{m,hn} \right),
\end{align*}
\]

where \(p^3_{m,hn} = P_{t,m} |c_{m,hn}|^2 + \sigma^2, \quad p^3_{m,mn} = \upsilon_5 P_{m,hn} |c_{m,hn}|^2 - \sigma^2, \quad p^4_{m,hn} = \psi_5 P_{m,hn} |c_{m,hn}|^2 - \sigma^2, \quad p^4_{m,mn} = \Theta P_{m,mn} |c_{m,mn}|^2 + \sigma^2.
\]

Proof: The proof of the Theorem 3 is identical to that in Appendix B.

2) CUAV POWER ALLOCATION

Based on (26), we obtain the minimum transmission power of CUAV within a range of \(P_{u,u}\). Thus, we can reformulate the suboptimisation problem as follows:

\[
\begin{align*}
\min_{P_{u,hn}, P_{u,mn}} & \quad P_{u,hn} + P_{u,mn} \\
\text{s.t.} \quad & \quad \Psi_{d,a}^{A} T_{u,hc}^{1} \geq T_{u,hc}^{1}, \\
& \quad \Psi_{d,a}^{A} T_{u,mn}^{1} \geq T_{u,mn}^{1},
\end{align*}
\]  
\[
(29a)
\]
\[
(29b)
\]
\[
(29c)
\]

\[
\begin{align*}
(P_{u,hn} + P_{u,mn}) |c_{u,p}|^2 \leq I_{th}, \quad \forall p \in N_p, \\
P_{u,hn} + P_{u,mn} \leq P_{t,u}, \\
P_{u,mn} \leq P_{u,hn}.
\end{align*}
\]  
\[
(29d)
\]
\[
(29e)
\]
\[
(29f)
\]

Here, the objective function (29a) with constraints (29d), (29e), and (29f) are linear functions of two positive parameters, namely \(P_{u,u}\) and \(P_{u,mn}\). Next, the constraints (29b) and (29c) are both non-convex functions, which makes this subproblem a non-convex function. The proof is similar to that in Appendix A. After modifying the constraints (29b) and (29c), we find the subproblem (29) as follows:

\[
\begin{align*}
\min_{P_{u,hn}, P_{u,mn}} & \quad P_{u,hn} + P_{u,mn} \\
\text{s.t.} \quad & \quad P_{u,mn} |c_{u,hn}|^2 + P_{u,mn} |c_{u,mn}|^2 + \sigma^2 \\
& \quad \psi_7 P_{u,hn} |c_{u,hn}|^2 \leq 0, \\
& \quad \Theta P_{u,hn} |c_{u,mn}|^2 + P_{u,mn} |c_{u,mn}|^2 + \sigma^2 \\
& \quad \psi_8 P_{u,mn} |c_{u,mn}|^2 \leq 0,
\end{align*}
\]  
\[
(30a)
\]
\[
(30b)
\]
\[
(30c)
\]
\[
(30d)
\]

where \(\psi_7 = 1/(2(1-\Psi_{d,a}^{A})^B - 1)\) and \(\psi_8 = 1/(2(1-\Psi_{d,a}^{A})^B - 1)\). Subproblem (30) can be realised as a linear optimisation problem and the optimal solutions are provided in Theorem 4.

Theorem 4: The optimal power allocations of CUAV to problem (30) for HP and MP signals in interference case can be expressed as

\[
\begin{align*}
P^{*u,hn} & = \min \left( p^{56}_{u,hn}, p^{78}_{u,hn} \right), \\
P^{*u,mn} & = \min \left( p^{56}_{u,mn}, p^{78}_{u,mn} \right),
\end{align*}
\]

where \(p^{56}_{u,hn} = \max \left( p^5_{u,hn} p^6_{u,hn} \right), \quad p^{78}_{u,hn} = \max \left( p^7_{u,mn}, p^8_{u,mn} \right), \quad p^5_{u,hn} = P_{u,mn} |c_{u,hn}|^2 + P_{u,mn} |c_{u,mn}|^2 + \sigma^2, \quad (1+\upsilon_7) |c_{u,hn}|^2, \\
\]
\[
(30e)
\]
\[
(30f)
\]

Proof: The proof of the Theorem 4 is similar to that in Appendix C.
Based on the suboptimisation problem (28) and (30), the final procedure is described in Algorithm TPA 2 below:

**TPA 2: Transmit Power Allocation Algorithm for Interference Case**

1. **Input:** Initial parameters given in Table 1;
2. for all \( n \in \mathcal{N}_i \) do
3. Decompose the problem (26) into (28) and (30);
4. Compute the optimal solutions such as \( P^3_{m,hn} \) and \( P^3_{m,nn} \) based on Theorem 3;
5. \( P_{mn} = P^3_{m,hn} + P^3_{m,nn} \);
6. Compute the optimal solutions such as \( P^4_{u,hn} \) and \( P^4_{u,nn} \) based on Theorem 4;
7. \( \xi^1_n \leftarrow P^3_{m,hn}, P^3_{m,nn}, P^4_{u,hn}, \text{ and } P^4_{u,nn} \);
8. end for
9. **Output:** \( \xi^1_n(P^3_{m,hn}, P^3_{m,nn}, P^4_{u,hn}, P^4_{u,nn}) \) for \( \forall n \in \mathcal{N}_i \);

**C. COMPLEXITY ANALYSIS**

This section describes the overall complexity of the proposed method. Both the CUAV and the MBS have implemented the proposed approach. For the effectual case, the complexity of the proposed method is \( O_1(A_1 + (N_{sh} + N_{sm})A_2) \), where \( A_1 \) is the arithmetic operation of the optimal solution at MBS and \( A_2 \) is the arithmetic operation of the optimal solution at CUAV. For the interference case, the complexity of the proposed method is \( O_2(A_1 + (N_{sh} + N_{sm})A_2 + A_3) \), where \( A_3 \) is the arithmetic operation of optimum solution summation.

**V. SIMULATION RESULTS**

In this section, numerical results are provided to validate the performance of the proposed algorithms in CUAV-assisted NOMA networks. In the simulation, the CUAV and MBS are located at the following coordinates in metres: CUAV = (150, 150, 300) and MBS = (500, 500, 40). Our CUAV is a quadcopter. For the simple design, 20 PUs,\(^4\) 20 SU-HPs,\(^5\) and 20 SU-MPs\(^5\) were deployed to serve randomly located in an area of \( 600 \times 600 \times 300 \) m\(^3\), as shown in Fig. 2. For suburban, urban, and dense urban areas, the simulation parameters are listed in Table 1. To study the average energy efficiency performance, we adopted the CUAV-to-MBS/PU channel utilised in Eqs. (7), (8), (9), (10), and (11), the CUAV-to-SU channel utilised in Eqs. (7), (8), (9), (10), (11), and (12), the MBS-to-PU channel utilised in Eqs. (7), (8), and (13), and the MBS-to-SU channel utilised in Eqs. (7), (8), (13), and (14) with a carrier frequency of 5.5 GHz. In these simulations, the average energy efficiency (bits/J) was calculated by using the mean value of energy efficiency.

Moreover, the average latency (ms) was calculated by using the mean value of latency.\(^6\)

**A. EFFECTUAL ENERGY EFFICIENCY AND LATENCY**

In Fig. 3, we obtain the average energy efficiency against the CUAV height over the suburban, urban, and dense urban areas in the effectual state. To start with, in the suburban area, the energy efficiency value gradually increases until 81 m, where the energy efficiency value is at its peak with 12463 bits/J, and then decreases gradually with the increasing height of the CUAV. As there are fewer obstacles and building comparatively, the CUAV needs less power to communicate; thus, the energy efficiency level decreases with increasing height. Next, in urban areas, as height increases, the efficiency rate steadily increases because the density of the obstacles increases.\(^6\)

\(^4\) PUs are randomly displaced outside a five-story hospital building with a height between 0 m and 20 m.

\(^5\) SU-HPs and SU-MPs are randomly displaced inside a five-story hospital building with a height between 0 m and 20 m.

\(^6\) The time it takes for a communication connection, such as an MBS-CUAV-SU-HP/SU-MP, to send or receive data is known as its latency.
TABLE 1. Simulation parameters.

| Parameter | Value | Parameter | Value | Parameter | Value | Parameter | Value |
|-----------|-------|-----------|-------|-----------|-------|-----------|-------|
| $m_{ba} [kg]$ | 1.07  | $m_{ba} [kg]$ | 1      | $m_{pa} [kg]$ | 0.5  | $g_{rs} [\text{m/s}]$ | 9.81/4 |
| $C_{ba}$ | 1.49  | $C_{ba}$ | 1      | $C_{pa}$ | 2.2  | $A_{bo} [\text{m}^2]$ | 0.0599 |
| $A_{bo} [\text{m}^4]$ | 0.0135 | $D_m [\text{m}]$ | 1      | $v_0 [\text{m/s}]$ | 20   | $K$ | 0.1 |
| $t_{fu} [\text{ms}]$ | 0.125 | $\rho_{fu} \rho_{de}$ | 0.1/0.9 | $\rho_p (\omega = 1)$ | 0.5  | $f_{ca} [\text{GHz}]$ | 5.5  |
| $\alpha_{wait}$ | 0.5   | $n_{wait}$ | 5     | $L_{wall} [\text{dB}]$ | 4.9  | $P_{ru} [\text{W}]$ | 1 |
| $\alpha_{LoS}$ | 0.1   | $\alpha_{LoS}$ | 1      | $\alpha_{LoS}$ | 1.6  | $T_{ru,mc} [\text{Kbps}]$ | 10 |
| $\alpha_{NLoS}$ | 21    | $\alpha_{NLoS}$ | 20     | $\alpha_{NLoS}$ | 23   | $T_{ru,mc} [\text{Kbps}]$ | 10 |
| $\psi$ | 0.35  | $\psi$ | 0.18  | $\psi$ | 0.14  | $T_{ru,mc} [\text{Kbps}]$ | 10 |
| $I_{th} [\text{dBm}]$ | -70   | $B [\text{MHz}]$ | 0.1/0.5 | $B$ | 10  | $P_r [\text{W}]$ | 1 |

1, 2, and 3 are considered for urban, and dense-urban areas. 4 and 5 are considered for sub-urban, urban, and dense-urban areas.

Building is greater than that of suburban areas. At 150 m, the energy efficiency is at an optimal point in urban areas with 9383.78 bits/J. Similarly, for densely urban areas, the energy efficiency increases with increasing height. However, both the average energy efficiencies in the urban and densely urban areas are lower than those in suburban areas, as there are fewer obstacles to cause interference and fading issues.

In Fig. 4, the average energy efficiency with probability of requesting data served by the CUAV ($\Psi_{d,n}^{cu}$) in the effectual state over suburban, urban, and densely urban regions. The value of $\Psi_{d,n}^{cu}$ ranges from 0 to 1. For the three regions, the energy efficiency first increases and then decreases as the $\Psi_{d,n}^{cu}$ increases. This is because at initial most popular contents requested by the SUs will be cached at the CUAV, and upon request, the CUAV can optimally send the requested data swiftly, which will ensure higher energy efficiency. Moreover, the energy efficiency decreases when the requesting data served by MBS increases. At $\Psi_{d,n}^{cu} = 0.5$, the energy efficiency values are 7326.7 bits/J, 7202.67 bits/J, and 7008.44 bits/J for the suburban, urban, and dense urban regions, respectively.

Fig. 5 depicts the average energy efficiency at different interference threshold ($I_{th}$) in the effectual state over suburban, urban, and dense urban areas. PUs and SUs use the same carriers in the cognitive environment. Therefore, reciprocal interaction occurs between PUs and SUs for the imperfect identification of the idle channel. As CUAV can produce dangerous PU interference, CUAV communication needs to be monitored and controlled. Thus, to protect PUs, CUAV transmission is below a specific $I_{th}$. Initially, the energy efficiency is constant, and after $I_{th} = -90$ dBm, it rises with increasing $I_{th}$ because the transmission power increases, as shown in (24d) and (29d). Also, it is observed that when $I_{th}$ is large (e.g., $-70$ dBm), the energy efficiency values of all areas are constant. This is because the total transmit power budget dominates the interference threshold constraint. Therefore, the transmission power of the CUAV should be controlled. In addition, the energy efficiency values are 7567.72 bits/J, 7257.21 bits/J, and 6938.47 bits/J at $I_{th} = -50$ dBm in suburban, urban, and dense urban areas, respectively.

Fig. 6 shows the average effectual latency at different SIC coefficient points over suburban, urban, and dense urban...
areas. The SIC coefficient ($\Theta$) represents the perfect (i.e. $\Theta = 0$) and imperfect (i.e. $\Theta = 1$) SIC process, and it ranges from $0$ to $1$. The effectual latency is defined as $L_{\text{on}}^0 = \frac{N_{\text{bit}}}{ET_{\text{on}}^0 + ET_{\text{on}}^0}$, where $N_{\text{bit}}$, $ET_{\text{on}}^0$, and $ET_{\text{on}}^0$ are the number of bits, the effectual throughput of SU-HP, and the effectual throughput of SU-MP, respectively. At $\Theta = 0.5$, the average latency in suburban, urban, and dense urban areas is $0.183$ m/s, $0.185$ m/s, and $0.188$ m/s, respectively. In addition, these values indicate that in suburban areas, there is less interference and fading compared to urban and dense urban areas; thus, latency is low. This is because the effectual throughput is high. Moreover, as the SIC coefficient increases, the average latency gradually increases because a higher SIC coefficient value represents a more imperfect SIC process.

**B. INTERFERENCE ENERGY EFFICIENCY AND LATENCY**

Similar to Fig. 3, Fig. 7 illustrates the average energy efficiency in the interference state over suburban, urban, and dense urban areas. Here, all energy efficiency values of all areas will be significantly lower than that of the effectual state because MBS might be communicating with the CUAV causing external interference. Thus, the CUAV will operate at a higher power to maintain performance; consequently, there will be a decrease in the energy efficiency level. In suburban areas, the efficiency value is at its maximum with $2147.88$ bits/J at a height of $83$ m, which is still lower than the efficiency value in suburban areas in the effectual state. Subsequently, in urban areas, the CUAV performs with $1690.1$ bits/J optimum energy efficiency at a height of $158$ m. Finally, in densely urban areas, the efficiency level is the lowest among all other areas; for a higher number of buildings and users with added interference from the MBS, the CUAV utilises considerable power to optimise its throughput, thus reducing energy efficiency. At $204$ m height, we obtain an energy efficiency value of $1454.46$ bits/J in dense urban area.

Similarly in Fig. 4, Fig. 8 shows the average energy efficiency with different $\Psi_{d,n}^c$ for the active interference of MBSs over similar regions. All energy efficiency plots increase with increasing $\Psi_{d,n}^c$ at initial and then decrease with increasing $\Psi_{d,n}^c$. In the suburban areas, at $0.5 \Psi_{d,n}^c$, the efficiency value is $1455.33$ bits/J, which is again significantly lower than the value achieved in the effectual state. Next, in urban and densely urban regions at $0.5 \Psi_{d,n}^c$, the energy efficiencies are $1426.68$ bits/J, and $1379.07$ bits/J. Specifically, the urban energy efficiency level is higher than the energy efficiency of the densely urban region, but both have overall lower efficiency than the suburban areas.

Likewise Fig. 5, Fig. 9 shows the energy efficiency at different $I_{th}$ in the interference state over suburban, urban, and dense urban regions. As the MBS will interfere with the CUAV communication, all efficiency levels will be lower. The energy efficiency values are $1493.81$ bits/J, $1433.29$ bits/J, and $1353.8$ bits/J at $I_{th} = -50$ dBm in suburban, urban, and dense urban areas, respectively.

Fig. 10 shows the average interference latency at different SIC coefficients. The interference latency is defined as
and dense urban regions, with regard to the CUAV height, probability of requesting data served by CUAV, interference temperature threshold, and SIC coefficient as the compression criteria.

- **CUAV height:** With regard to the CUAV height at 150 m from Figs. 3 and 7, 447.595%, 457.602%, and 481.655% enhancement over suburban, urban, and dense urban areas, respectively, the effectual state has a better energy efficiency performance than the interference state.

- **Probability of requesting data served by CUAV:** At a 0.5 probability of requesting data served by CUAV from Figs. 4 and 8, the effectual state has an efficiency improvement of 406.605% in suburban areas, 406.332% in urban areas, and 412.518% in densely urban regions.

- **Interference temperature threshold:** With regard to interference temperature from Figs. 5 and 9, at a -50 dBm standard point, the energy efficiency in the effectual state has a 406.605%, 406.332%, and 412.518% improvement over the energy efficiency of the interference state.

- **SIC coefficient:** Concerning the SIC coefficient at 0.5 from Figs. 6 and 10, the effectual state has a lower energy efficiency than the interference state with 396.276%, 397.837%, and 398.907% improvement over the suburban, urban, and dense urban regions, respectively.

### D. COMPARISON OF OMA AND NOMA SCHEMES

We evaluate our proposed NOMA system with the OMA system to demonstrate its efficacy. This design is identical to the proposed design except that it caches and dispatches using the OMA scheme rather than the NOMA scheme. The bandwidth is evenly shared and allotted to SU-HP and SU-MP devices under the OMA system. Moreover, each device is assigned an orthogonal bandwidth allocation, ensuring that SU-HP and SU-MP devices do not interfere with one another.

In Fig. 11, we plot the average energy efficiency at various CUAV heights for NOMA and OMA methods over suburban, urban, and dense urban regions in the effectual state. It is worth noting from the figure that the performance of NOMA scheme CUAV networks outperforms that of traditional OMA scheme CUAV networks. From the numerical point of view, we can see that over the height of 81 m the maximum energy efficiency achieved by the CUAV with NOMA method is 12463 bits/J for the suburban region. With the OMA method, the CUAV reaches up to 9129.26 bits/J at 80 height, which is significantly lower than the NOMA method. Moreover, for the urban region at 150 m height, the CUAV can perform up to 9383.78 bits/J in the NOMA method, which is significantly better than the OMA method at similar height. Likewise, for the dense urban region where the NOMA method still manages to outperform the OMA method. Overall, as CUAV height grows, the performance deterioration of the OMA method becomes more significant than that of NOMA method, confirming the benefits of the NOMA transmission system.
FIGURE 11. Comparison of average energy efficiency with OMA scheme at different CUAV heights in effectual state.

FIGURE 12. Comparison of average energy efficiency with OMA scheme at different CUAV heights in interference state.

For the interference state, we similarly plot the average energy efficiency at various CUAV heights for NOMA and OMA methods over suburban, urban, and dense urban regions in Fig. 12. Here for the suburban region, at 83 m CUAV height the NOMA enhanced average energy efficiency is optimal with 2147.88 bits/J and is significantly better than the energy efficiency (1051.81 bits/J) achieved by the OMA method at that similar height. In the urban region both the NOMA and OMA methods give lesser energy efficiency values such as 1682.88 bits/J and 824.89 bits/J at 150 m height. Similarly, for the densely urban region, the CUAV performs optimally with NOMA method than OMA at all height scenarios.

E. BENCHMARK SCHEMES

Since there are no relevant benchmark schemes in the literature, we evaluate the proposed approach with the following benchmark schemes:

- **Fixed power MBS**: At the MBS, we assign equal power to HP and MP information for this scheme. Based on Theorems 2 and 4, CUAV employs the optimum power for HP and MP information.

- **Fixed power CUAV**: At the CUAV, we assign equal power to HP and MP information for this scheme. Based on Theorems 1 and 3, MBS employs the optimum power for HP and MP information.

- **Both fixed power**: We assign equal power to HP and MP information at both the MBS and the CUAV for this scheme.

Fig. 13 shows the average energy efficiency in the effectual state at various SIC coefficients in urban area. The energy efficiency decays with SIC coefficients increase in three areas. Fig. 13 also reveals that the proposed scheme outperforms the considered benchmark schemes. At 0.5 SIC coefficient, the values of energy efficiency for the proposed scheme, the fixed power MBS, both fixed power, and the fixed power CUAV are 7182.50 bits/J, 6809.45 bits/J, 3252.87 bits/J, and 2370.31 bits/J, respectively. The proposed scheme improves the fixed power MBS by 5.48%, both fixed power by 120.80%, and the fixed power CUAV by 203.02%, respectively. We also see that the energy efficiency for both fixed power is high compared to fixed power CUAV. This is due to the fact that the optimum power of MBS is less than its fixed power.

Fig. 14 shows the average energy efficiency plots at various SIC coefficients in interference state at the same area, as shown in Fig. 13 for the effectual state. Likewise, in the interference state, all efficiency values are lower than those of the effectual state. The plot for the interference state is similar to the plot for the effectual state except for the proposed scheme and fixed power MBS. When the value of the SIC coefficient is lower than 0.2, the fixed power of MBS is better than the proposed scheme. This is because the optimal power of MBS is higher than the fixed power of MBS. At 0.5 SIC coefficient, the values of energy efficiency for the proposed scheme, the fixed power MBS, both fixed power, and the fixed power CUAV are 1404.20 bits/J, 1398.62 bits/J,
topology-aware routing protocol that provides dependable source-to-destination pairings [42]. Moreover, we save our proposed system from malicious user attacks using a friend or foe detection technique with physical layer network coding [43].

**APPENDIX A**

**PROOF OF SUBOPTIMISATION PROBLEM (22)**

The constraint (22b) can be represented as

\[
\mathcal{L}_1(P_{m,hn}, P_{m,mn}) = (1 - \Psi_{d,n}^{cu}) T_{m,hn}^0 - T_{m,mc}^0. \tag{A.1}
\]

Now, the second-order derivative of (A.1) with respect to \( P_{m,hn} \) and \( P_{m,mn} \), the mathematical expression is written as

\[
\frac{\partial^2 \mathcal{L}_1}{\partial P_{m,hn}^2} = -\frac{\delta_c |c_{mn,hu}|^4}{\log(2) (\delta_d)^2 (\delta_b)^2}, \tag{A.2}
\]

\[
\frac{\partial^2 \mathcal{L}_1}{\partial P_{m,mn}^2} = \frac{\delta_i P_{m,mn} |c_{mn,hu}|^6}{\log(2) (\delta_d)^3 \delta_b^3} \left( 2 - \frac{P_{m,mn} |c_{mn,hu}|^2}{\delta_d \delta_b} \right), \tag{A.3}
\]

where \( \delta_d = \sigma^2 + P_{m,mn} |c_{mn,hu}|^2, \delta_b = \left( 1 + \frac{P_{m,mn} |c_{mn,hu}|^2}{\delta_c} \right), \) and \( \delta_c = (1 - \Psi_{d,n}^{cu}) T_{m,mc}. \) From (A.2), it can be easily observed that the determinant is less than zero; thus, (A.1) is non-convex with respect to \( P_{m,hn} \). However, as can be seen from (A.3) that the determinant is less than zero if \( \frac{P_{m,mn} |c_{mn,hu}|^2}{\delta_d \delta_b} > 2 \). Hence, (A.1) is convex or non-convex with respect to \( P_{m,mn} \) depending on \( \delta_d, \delta_b \), and \( |c_{mn,hu}|^2 \).

The constraint (22c) can be represented as

\[
\mathcal{L}_2(P_{m,hn}, P_{m,mn}) = (1 - \Psi_{d,n}^{cu}) T_{m,mn}^0 - T_{m,mc}^0. \tag{A.4}
\]

Now, the second-order derivative of (A.4) with respect to \( P_{m,hn} \) and \( P_{m,mn} \), the mathematical expression is written as

\[
\frac{\partial^2 \mathcal{L}_2}{\partial P_{m,hn}^2} = \frac{\delta_{cc} |c_{mn,hu}|^2}{\log(2) (\delta_d)^2 \delta_e} \left( 2 - \frac{P_{m,mn} |c_{mn,hu}|^2}{\delta_d \delta_e} \right), \tag{A.5}
\]

\[
\frac{\partial^2 \mathcal{L}_2}{\partial P_{m,mn}^2} = -\frac{\delta_c |c_{mn,hu}|^4}{\log(2) (\delta_d)^2 (\delta_e)^2}, \tag{A.6}
\]

where \( \delta_{cc} = \delta_i P_{m,hn} |c_{mn,hu}|^2, \delta_d = \sigma^2 + \Theta P_{m,hn} |c_{mn,hu}|^2, \delta_d = \left( 1 + \frac{P_{m,mn} |c_{mn,hu}|^2}{\delta_d \delta_b} \right). \) From (A.6), it can be easily observed that the determinant is less than zero; thus, (A.4) is non-convex with respect to \( P_{m,mn} \). However, we can also see from (A.5) that the determinant is less than zero if \( \frac{P_{m,mn} |c_{mn,hu}|^2}{\delta_d \delta_b} > 2 \). Hence, (A.4) is convex or non-convex with respect to \( P_{m,hn} \) depending on \( \delta_d, \delta_e \), and \( |c_{mn,hu}|^2 \).

**APPENDIX B**

**PROOF OF SUBOPTIMISATION PROBLEM (23)**

The Lagrangian approach [44] provides the solution to the optimisation problem stated in (23) can be

365.64 bits/J, and 292.06 bits/J, respectively. The proposed scheme improves the fixed power MBS, both fixed power and fixed power CUAV by 0.40%, 284.04%, and 380.80%, respectively.

**VI. CONCLUSION AND FUTURE WORK**

To summarise, we herein develop an energy-efficient communication framework that processes two types of sensing data (i.e., HP and MP) through a cache-enabled CUAV to serve the information requests of SUs through the NOMA method in three regions. To further support this, we consider two states (i.e., effectual and interference) concerning any interference from MBSs and then derive the throughput and energy efficiency expressions in the downlink scenario. Moreover, we formulate an optimisation problem for effectual and interference to minimise the transmission power of CUAV and MBS and enhance the overall performance of the CUAV when serving any SUs. In addition, our simulation results demonstrate that in suburban, urban, and densely urban regions, the average energy efficiency for the effectual state renders higher performance than the energy efficiency achieved in the interference state, ensuring that the CUAV optimally serves the SU requests.

Although CUAV has become increasingly complex and efficient by using technological improvements, the proposed approach has some limitations. As CUAVs gain popularity, privacy concerns have grown. The CUAV’s control system may be targeted, and hackers can collect HP and MP device information. Cold temperatures in an area reduce CUAV battery life, hence an efficient battery is needed. Aforementioned the limitations, several future developments of such communication models are possible if we employ an energy harvesting technique for the CUAV operation and transmit antenna selection method [40], [41], allowing the CUAV-based entire system to optimally adjust the data rate and energy efficiency depending on the communication criteria. In addition, we investigate a Q-learning-based

![FIGURE 14. Comparing the average energy efficiency at various SIC coefficients with benchmarking schemes in interference state.](image-url)
represented as
\[\mathcal{L}_3(P_{m,hn}, P_{m,mn}) = P_{m,hn} + P_{m,mn} + \delta_e (P_{m,mn}) \]
\[\cdot |c_{m,hn}|^2 + \alpha^2 - \nu_1 P_{m,hn} |c_{m,hn}|^2 + \delta_f \Theta P_{m,hn} \]
\[\cdot |c_{m,mn}|^2 + \alpha^2 - \nu_2 P_{m,mn} |c_{m,mn}|^2 + \delta_g \Theta P_{m,mn} \]
\[+ P_{m,mn} - P_{t,m} + \delta_h (P_{m,mn} - P_{m,hn}), \quad (B.1)\]
where \(\delta_e, \delta_f, \delta_g,\) and \(\delta_h\) are positive variables for the constraints given in (23b)-(23d).

The Karush-Kuhn-Tucker (KKT) conditions are necessary to obtain optimal solution, and the following KKT conditions are
\[\delta_e \geq 0, \delta_f \geq 0, \delta_g \geq 0, \delta_h \geq 0, \]
\[\delta_e (P_{m,mn} |c_{m,mn}|^2 + \alpha^2 - \nu_1 P_{m,hn} |c_{m,hn}|^2), \]
\[\delta_f (\Theta P_{m,hn} |c_{m,hn}|^2 + \alpha^2 - \nu_2 P_{m,mn} |c_{m,mn}|^2), \]
\[\delta_g (P_{m,mn} - P_{t,m}), \]
\[\frac{d\mathcal{L}_3(P_{m,hn}, P_{m,mn})}{dP_{m,hn}} = 0, \frac{d\mathcal{L}_3(P_{m,mn}, P_{m,mn})}{dP_{m,mn}} = 0, \]
\[\frac{d\mathcal{L}_3(P_{m,hn}, P_{m,mn})}{dP_{m,mn}} = 0, \frac{d\mathcal{L}_3(P_{m,mn}, P_{m,mn})}{dP_{m,mn}} = 0, \]
\[\frac{d\mathcal{L}_3(P_{m,hn}, P_{m,mn})}{dP_{m,mn}} = 0, \frac{d\mathcal{L}_3(P_{m,mn}, P_{m,mn})}{dP_{m,mn}} = 0. \]
\[\quad (B.2)\]

From (B.2), we get
\[P_{m,mn} |c_{m,hn}|^2 + \alpha^2 - \nu_1 P_{m,hn} |c_{m,hn}|^2 = 0, \quad (B.3)\]
\[\Theta P_{m,hn} |c_{m,mn}|^2 + \alpha^2 - \nu_2 P_{m,mn} |c_{m,mn}|^2 = 0, \quad (B.4)\]
\[P_{m,hn} + P_{m,mn} = P_{t,m}. \quad (B.5)\]

After some manipulations from (B.3) and (B.5), we have
\[p_{1,m,hn} = \frac{|c_{m,hn}|^2 + \alpha^2}{1 + \nu_1} |c_{m,hn}|^2. \quad (B.6a)\]
\[p_{1,m,mn} = \frac{\nu_1 |c_{m,mn}|^2 - \alpha^2}{1 + \nu_1} |c_{m,mn}|^2. \quad (B.6b)\]

After some manipulations from (B.4) and (B.5), we have
\[p_{2,m,hn} = \frac{\nu_2 |c_{m,hn}|^2 - \alpha^2}{(\nu_2 + \Theta)} |c_{m,mn}|^2. \quad (B.7a)\]
\[p_{2,m,mn} = \frac{\Theta |c_{m,mn}|^2 + \alpha^2}{(\nu_2 + \Theta)} |c_{m,mn}|^2. \quad (B.7b)\]

From (B.6) and (B.7), we obtain the optimal power allocation as follows
\[p_{1,m,hn}^{1*} = \max \left(p_{1,m,hn}, p_{m,mn}^2\right), \quad \]
\[p_{1,m,mn}^{1*} = \min \left(p_{1,m,mn}, p_{m,mn}^2\right). \quad (C.1)\]

**APPENDIX C**

**PROOF OF SUBOPTIMISATION PROBLEM (25)**

The Lagrangian approach [44] provides the solution to the optimisation problem stated in (25) can be represented as
\[\mathcal{L}_4(P_{u,hn}, P_{u,mn})\]
\[= P_{u,hn} + P_{u,mn} + \delta_i \left(P_{u,mn} |c_{u,hn}|^2 \right)\]
\[+ \nu_3 P_{u,hn} |c_{u,hn}|^2) + \delta_j \left(\Theta P_{u,hn} |c_{u,mn}|^2 + \alpha^2 \right) \]
\[- \nu_3 P_{u,mn} |c_{u,mn}|^2) \right) + \delta_k \left(\left[P_{u,hn} + P_{u,mn}\right] |c_{u,p}|^2 \right) \]
\[- I_{th} + \delta_l \left(P_{u,hn} + P_{u,mn} - P_{t,u}\right) + \delta_m \left(\left[P_{u,mn} - P_{u,hn}\right]\right). \quad (C.1)\]

where \(\delta_i, \delta_j, \delta_k, \delta_l,\) and \(\delta_m\) are positive variables for the constraints given in (25b)-(25d).

The KKT conditions are necessary to obtain optimal solution, and the following KKT conditions are
\[\delta_i \geq 0, \delta_j \geq 0, \delta_k \geq 0, \delta_l \geq 0, \delta_m \geq 0, \]
\[\delta_i \left(P_{u,mn} |c_{u,hn}|^2 + \alpha^2 - \nu_3 P_{u,hn} |c_{u,hn}|^2) \right)\]
\[\delta_j \left(\Theta P_{u,hn} |c_{u,mn}|^2 + \alpha^2 - \nu_3 P_{u,mn} |c_{u,mn}|^2) \right) \]
\[\delta_k \left(\left[P_{u,hn} + P_{u,mn}\right] |c_{u,p}|^2 - I_{th}\right), \]
\[\delta_l \left(P_{u,hn} + P_{u,mn} - P_{t,u}\right), \]
\[\delta_m \left(P_{u,mn} - P_{u,hn}\right). \quad (C.2)\]

From (C.2), we get
\[P_{u,mn} |c_{u,hn}|^2 + \alpha^2 - \nu_3 P_{u,hn} |c_{u,hn}|^2 = 0, \quad (C.3)\]
\[\Theta P_{u,hn} |c_{u,mn}|^2 + \alpha^2 - \nu_3 P_{u,mn} |c_{u,mn}|^2 = 0, \quad (C.4)\]
\[\left[P_{u,hn} + P_{u,mn}\right] |c_{u,p}|^2 = I_{th}, \quad (C.5)\]
\[P_{u,hn} + P_{u,mn} = P_{t,u}. \quad (C.6)\]

After some manipulations from (C.3) and (C.6), we have
\[p_{1,u,hn} = \frac{|c_{u,hn}|^2 + \alpha^2}{(1 + \nu_3) |c_{u,hn}|^2}. \quad (C.7a)\]
\[p_{1,u,mn} = \frac{\nu_3 |c_{u,mn}|^2 - \alpha^2}{(1 + \nu_3) |c_{u,mn}|^2}. \quad (C.7b)\]

After some manipulations from (C.4) and (C.6), we have
\[p_{2,u,hn} = \frac{\nu_3 |c_{u,hn}|^2 - \alpha^2}{(1 + \nu_3) |c_{u,hn}|^2}. \quad (C.8a)\]
After some manipulations from (C.3) and (C.5), we have

\[ P_{u,hn}^3 = \frac{\nu_4 I_h \left| c_{u,hn} \right|^2 - \left| c_{u,p} \right|^2 \sigma^2}{\nu_4 I_h \left| c_{u,hn} \right|^2 - \left| c_{u,p} \right|^2 (1 + \nu_3)} \]  

(8.9b)

After some manipulations from (C.4) and (C.5), we have

\[ P_{u,hn}^4 = \frac{\nu_4 I_h \left| c_{u,hn} \right|^2 - \left| c_{u,p} \right|^2 \sigma^2}{\nu_4 I_h \left| c_{u,hn} \right|^2 - \left| c_{u,p} \right|^2 (1 + \nu_3)} \]  

(10.10a)

\[ P_{u,mm}^4 = \frac{\nu_4 I_h \left| c_{u,mm} \right|^2 + \left| c_{u,p} \right|^2 \sigma^2}{\nu_4 I_h \left| c_{u,mm} \right|^2 - \left| c_{u,p} \right|^2 (1 + \nu_3)} \]  

(10.10b)

From (C.7), (C.8), (C.9), and (C.10), we obtain the optimal power allocation as follows

\[ P_{a,hn}^2 = \min\left(P_{a,hn}^{12}, P_{a,hn}^{34}\right) \]

\[ P_{a,mm}^2 = \min\left(P_{a,mm}^{12}, P_{a,mm}^{34}\right) \]

where

\[ P_{a,hn}^{12} = \max\left(P_{a,hn}^{1}, P_{a,hn}^{2}\right), P_{a,mm}^{34} = \max\left(P_{a,mm}^{3}, P_{a,mm}^{4}\right), \]

\[ P_{a,mm}^{12} = \max\left(P_{a,mm}^{1}, P_{a,mm}^{2}\right), P_{a,hn}^{34} = \max\left(P_{a,hn}^{3}, P_{a,hn}^{4}\right). \]

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