Multi-UAV Assisted IoT NOMA Uplink Communication System for Disaster Scenario

SUBHRAJIT BARICK AND CHETNA SINGHAL, (Senior Member, IEEE)
Department of Electronics and Electrical Communication Engineering, Indian Institute of Technology Kharagpur, Kharagpur, West Bengal 721302, India
Corresponding author: Subhrajit Barick (subhrajitbarick@iitkgp.ac.in)
This work was supported by the Indian Department of Science and Technology under Grant DST/INSPIRE/04/2015/000793.

ABSTRACT Unmanned aerial vehicle (UAV) communication has become a prominent technology that can effectively assist in IoT systems. The inherent features of UAV such as mobility, flexibility, and fast deployment make it preferable for emergency Internet of Things (IoT) applications. In this paper, we consider a multi-UAV assisted wireless network to support uplink communication for IoT devices distributed over a disaster area. The network involves two types of UAVs: sector UAV (SU) and anchor UAV (AU). The SU hovers at a fixed height over the sector around the temporary base station (TBS), collects the information from the respective IoT devices and relays them to the TBS via AU. The AU revolves continuously around the TBS and relays the information between the SUs and TBS periodically. We aim to improve the uplink capacity of the system. To achieve this, we employ non-orthogonal multiple access (NOMA), where we jointly optimize the positions of SUs and the power control of IoT devices. We propose a two-step approach to solve this. First, we optimize the position of SU in each sector by minimizing the sum distances of SU from the respective IoT devices. Then, by considering the optimal SU location, we optimize the transmit power of IoT devices using Lagrange dual method. Finally, the experimental results show that the proposed scheme improves the system capacity by 22% compared to the state-of-the-art schemes.

INDEX TERMS UAV network, Internet of Things, uplink transmission, NOMA, system capacity.

I. INTRODUCTION

Internet of Things (IoT) has become a key component of modern age communication due to its ability to connect several devices, sensors, technologies, and applications [1]. The IoT architectures are widely used in several applications such as traffic management, healthcare facilities, surveillance, smart farming, and environment monitoring. However, reliable data transmission is a major challenge in most of the IoT applications [2]. This is because the IoT devices cannot transmit over long range due to their energy constraints. The data transmission is even more challenging during emergency situation such as natural disasters. During disaster, the conventional network may get damaged or overloaded, thus it is unable to serve all IoT devices. Therefore, in order to support the massive IoT requirements with limited resources, unmanned aerial vehicle (UAV) provides an effective solution. By using UAV-assisted wireless network, we can collect information from the dead zone IoT devices and efficiently transmit it to the remote data center [3], [4].

The UAV-assisted communication system has several advantages such as low cost, fast deployment, and strong line-of-sight (LOS) communication support. However, the limited UAV flight time is the major bottleneck in the system. In general, the UAV has a flight duration of less than one hour. Therefore, spectral efficiency is crucial for UAV-assisted communication. To address this, Non-orthogonal multiple access (NOMA) is found to be a favourable technology. It achieves spectral efficiency by allowing multiple devices to access the same spectrum simultaneously through successive interference cancellation (SIC) technology [5]. The use of NOMA in UAV network can improve the transmission efficiency of the communication system. So far, there are number of research works focusing on integration of NOMA in UAV communication [6]–[8]. A multi-UAV aided cellular network architecture in [6] is NOMA based with an aim to maximize the overall system capacity. To cope with the ever increasing data demands, millimeter-wave based NOMA-UAV network can improve the energy efficiency of the system [7]. A hybrid
structure with UAV-assisted network and ground base station (BS) cooperation can improve the system sum rate \[8\]. A time division multiple access (TDMA)-NOMA based hybrid multiple access scheme uses TDMA for UAV and NOMA for BS communication. Although NOMA-UAV system has several advantages, there exists challenges in implementation for scenarios with absent or damaged conventional network due to natural disaster.

In this work, we propose a NOMA-based multi-UAV assisted uplink communication system for IoT applications during disaster scenario. We consider that the data center is beyond the transmission range of IoT devices and present a novel system design to support the communication between the IoT devices and data server. The position of UAVs and the transmit power of IoT devices are jointly optimized to maximize the overall sum rate of the system. To resolve this, we follow a two step process. We first optimize the positions of UAVs for a given IoT distribution and then, by considering the optimal UAV positions, we decide the optimal transmitting power of IoT devices.

A. RELATED WORKS

Over past few years, many researchers have extensively studied the UAV communication for improving the performance of existing wireless networks. A detailed review of UAV applications for coverage enhancement is discussed in [9]–[11]. [9] introduces an optimal 3-D deployment strategy to maximize the UAV coverage. The authors consider a single UAV network and propose a framework, which decides the position of UAV in both horizontal and vertical dimensions to cover maximum users with minimum transmit power. A similar placement problem with multiple UAVs for coverage maximization is studied in [10] and [11]. In [10], the authors use the circle packing theory to find the optimal positions of multiple UAVs in 3D space, whereas [11] employs a successive placement approach to decide positions of UAVs. The throughput improvement of UAV assisted wireless network is considered in [12] and [13]. Both these works focus on multi-UAV network. [12] aims to maximize the user throughput by optimizing the user scheduling along with the UAVs’ trajectory and transmit power. However, [13] maximizes the overall system throughput through joint optimization of the user association, resource allocation and UAV placement. The use of UAV to support task offloading in an IoT scenario is discussed in [14]. The authors propose a novel UAV architecture to support the computing task of edge IoT nodes, where the UAV deployment and task scheduling are jointly optimized to improve the performance efficiency of the system.

All these works discussed so far focus on application of UAVs as BSs. However, the UAVs can also be used as relays to support long range communication, where no direct connectivity is available. The research on UAV-enabled relaying mainly covers two classes: static-UAV relaying and mobile-UAV relaying. The static-UAV relaying focuses on improving the performance of the communication system by optimizing the position of UAV relays, whereas the mobile-UAV relaying achieves the desired quality of service by controlling the mobility of UAV relays. [15] considers a static-UAV relaying in dense urban environment, where the authors optimize the relay position to maximize the downlink capacity of the system. Unlike simple UAV placement algorithm, this paper exploits the UAV-user propagation structure to decide the optimal UAV position. [16] considers a mobile-UAV relaying system, where the system capacity is maximized by jointly optimizing the relay trajectory and transmit power under mobility constraint and average transmit power constraint respectively. All these relaying discussed so far use single UAV relay and are useful for moderate range communication. As the distance increases, single-UAV relay may not be sufficient to provide reliable communication. To resolve this, multiple UAVs are used as relays. The throughput maximization of a multi-UAV relay network is studied in [17]. Here, the authors consider multiple static-UAV relays and optimize their positions to maximize the throughput of the system. The use of mobile-UAV for multi-hop relaying is considered in [18].

UAVs are also useful as data collectors in some applications. More specifically, in IoT system, where the sensors have limited power budget to transmit over long distance, the UAV-assisted data collection becomes a feasible solution. [19] presents a UAV-enabled data collection system for wireless sensor network (WSN), where the data collection is performed through a mobile-UAV. The trajectory of the UAV and the sensor’s wake-up schedule are jointly optimized to ensure reliable data collection with minimum energy consumption. To further improve the data collection efficiency of the UAV-enabled WSN, [20] proposes a novel multiple access scheme that uses code division multiple access (CDMA) to access ground sensor nodes. [21] considers a UAV-enabled ocean monitoring network (OMN) to collect information from underwater sensor nodes (USNs). The authors propose a novel architecture, in which the monitoring data sensed by USNs is first transmitted from USNs to the sink nodes (SNs) on the sea surface and then from the SNs, the information are transmitted to the ground base station via UAV node. The authors use a heuristic approach to find the optimal location of UAV and SNs aiming to improve the transmission efficiency of the system. However, all these system models discussed in [19]–[21] use single UAV for data collection, thus may not be suitable for large scale network. Therefore, [22] considers a multi-UAV enabled WSN, where the data collection is performed by following the time division multiple access (TDMA) principle. The trajectories of UAVs are jointly optimized with sensors’ wake-up scheduling to minimize the mission completion time. For improving data collection rate, [23] proposes a novel system design for UAV-enabled IoT network, where multiple UAVs are deployed to collect data from a time-varying IoT network by using frequency division multiple access (FDMA). The UAV-assisted data collection for heterogeneous wireless network is discussed in [24]. The authors propose a novel
resource allocation scheme, where the hovering altitude of UAVs and transmitting power of users are jointly optimized to maximize the overall system capacity.

All these works discussed so far use the orthogonal multiple access technique for resource allocation. However, with the increasing user requirements, it is essential to effectively utilize the available spectrum. NOMA is found to be a favourable technology to achieve high spectral efficiency and massive connection. The basic NOMA principles for cellular wireless network is discussed in [25]. With the aim to maximize the throughput, the authors propose a novel user clustering and power allocation strategy for both uplink and downlink network. [26] considers a NOMA-based UAV-assisted uplink IoT system, where the authors propose a novel subchannel assignment strategy to maximize throughput of the system. [27] analyzes the trade-off between the system throughput and proportional fairness of a UAV-NOMA communication system. Herein, the authors propose a novel power allocation strategy to maintain a balance between the system throughput and performance fairness. [28] proposes a framework for NOMA based UAV aided network to achieve high spectral efficiency and massive connections during emergency situation. The paper considers both single UAV and multi-UAV assisted networks and develops a joint trajectory and power optimization scheme to provide reliable services for both the cases. [29] introduces the Time Sharing NOMA (TS-NOMA) in UAV assisted communication to achieve high spectral efficiency and throughput fairness, whereas [30] implements the Cyclic-NOMA to ensure throughput fairness of the system. The application of Cyclic-NOMA for system sum rate maximization is explained in [31]. The overall sum rate of a Cyclic-NOMA based UAV-assisted network is maximized through joint optimization of UAV’s trajectory and user’s power allocation. [32] investigates the data collection in a NOMA-based UAV-assisted wireless sensor network. First, the authors develop a method to decide the optimal UAV position for effective data collection. Then, a NOMA based power control solution is proposed for sum rate maximization. The data collection in a NOMA-based multi-UAV assisted wireless sensor network is considered in [33]. The authors jointly optimize the flying height of UAVs and the transmit power of sensor nodes to improve the capacity of the system.

However, most of the UAV-assisted communication rely on the assumption that the serving UAVs should be within the coverage range of conventional network. However, this may not be feasible in all practical scenarios. In particular, when the conventional network is damaged due to the natural disaster, how to support the communication is the main focus of our work.

B. KEY CONTRIBUTIONS

The major contributions of this paper are listed as follows:

1) We propose a novel relay-based multi-UAV assisted uplink communication system design for IoT application during disaster scenario. Therein, we propose a hybrid multiple access scheme, which integrates NOMA with cyclical TDMA to enhance the transmission efficiency of the system.

2) We aim to maximize the overall system sum rate by jointly optimizing the positions of UAVs and transmit power of IoT devices. For this, we propose a two-step approach. First, we optimize the position of UAVs in the system. Then, for optimal UAV positions, we present a NOMA-based power control solution to maximize the system sum rate.

3) We conduct extensive simulations to evaluate the IoT uplink communication system with the proposed scheme and the results show that the proposed method performs satisfactorily compared with other schemes in terms of system sum rate.

The rest of the paper is organized as follows. Section II gives an overview of the system model and assumptions for the UAV-assisted uplink IoT system. This section also briefs about various channel models and data transmission models for both air-to-air and air-to-ground links in the network. Section III addresses the problem formulation. The resource allocation problem for sum rate maximization is solved in section IV. Section V evaluates the performance effectiveness of the proposed scheme and section VI concludes the article.

II. SYSTEM MODEL

We consider a UAV assisted IoT uplink communication system, where multiple UAVs are used to collect the real-time information from IoT devices that are distributed over a disaster area. As illustrated in Fig. 1, we consider a circular disaster region where all the base stations (BSs) are broken down. We place a temporary base station (TBS) at the center of the disaster region, which has a coverage range of radius \( r_0 \). IoT devices present within the coverage of TBS can directly transmit their information to the TBS, whereas we deploy a relay-based multi-UAV wireless network to collect information from the devices present outside the coverage.
range of TBS. The network involves two types of UAVs: sector UAV (SU) and anchor UAV (AU). The SU collects information from the remote IoT devices and the AU relays the information to the TBS.

The system involves $M$ SUs and one AU to serve $N$ IoT devices present outside the TBS coverage. Let $M = \{1, 2, \ldots, M\}$ and $N = \{1, 2, \ldots, N\}$ represent the set of SUs and IoT nodes respectively. All the UAVs are assumed to operate at a fixed height $h$ which corresponds to an acceptable height required for providing suitable coverage in a particular sector. Reducing $h$ improves the system capacity, but results in less coverage range. Instead, an increased $h$ improves the coverage range, but results in decreased capacity. We divide the disaster region outside the TBS coverage into $M$ sectors, where each sector is managed by one SU. We assume that each SU can serve a group of IoT nodes, whereas each IoT node can associate with only one SU, i.e., if $S_j$ represents the set of IoT nodes served by the sector UAV $SU_j$, then $\bigcup_{j=1}^{M} S_j = N$ and $s_{j_1} \cap s_{j_2} = \emptyset$, $\forall j_1, j_2 \in \mathcal{M}$, $j_1 \neq j_2$. Assuming that the sector $j$ contains $N_j$ IoT devices, denoted as $D_{j}^{(1)}$, $D_{j}^{(2)}$, $\ldots$, $D_{j}^{(N_j)}$, the set of devices is given as $N_j = \{1, 2, \ldots, N_j\}, j \in \mathcal{M}$. The uplink communication between IoT devices and central TBS is performed in two stages. In the first stage, each SU collects information from the respective IoT devices by employing NOMA and stores them in the buffer. Then, in the next stage, the SU re-transmits the stored information to the TBS via AU.

The AU is a fixed wing UAV, that continuously moves on a circular path centered at TBS with radius $r_0$ and revolution period $T$, and collects data from SUVs through cyclical TDMA.

The revolution period of AU, which is also the period of cyclical TDMA, is divided into $K$ time slots of equal duration. The time slot duration is selected based on the coherence time during which the communication channels are nearly static. The time slot duration is selected based on the coherence time $\tau$, such that $\tau = T/K$. Since, the AU moves between IoT device $D_{i}^{(j)}$ and central TBS is performed in two stages. In the first stage, each SU collects information from the respective IoT devices by employing NOMA and stores them in the buffer. Then, in the next stage, the SU re-transmits the stored information to the TBS via AU.

The mathematical symbols and their physical interpretation in Table 1.

### Table 1. Mathematical symbols.

| Symbol | Physical definition |
|--------|---------------------|
| $\mathcal{M}$ | Set of sector UAVs |
| $|\mathcal{M}| = M$ | Number of sector UAVs |
| $\mathcal{N}$ | Set of IoT devices |
| $|\mathcal{N}| = N$ | Number of IoT devices |
| $N_j$ | Number of IoT devices within sector $j$ |
| $W_j$ | Number of IoT devices associated with sector $j$ |
| $D_{j}^{(3)}$ | IoT device associated with sector $j$ |
| $SU_j$ | Sector UAV associated with sector $j$ |
| $h$ | Operating height of UAVs |
| $T$ | Revolution period of anchor UAV |
| $K$ | Set of time slots within the TDMA cycle |
| $K = K$ | Number of time slots within TDMA cycle |
| $\gamma$ | Duration of each time slot in the TDMA cycle |
| $M$ | Number of time frames within TDMA cycle |
| $L$ | Number of time slots within each time frame |
| $g_{i,j,k}$ | Channel gain between $D_{i}^{(j)}$ and $SU_j$ during time slot $k$ |
| $h_{i,j,k}$ | Channel power gain at reference distance of 1 m |
| $g_{i,j,k}$ | Fading coefficient between $D_{i}^{(j)}$ and $SU_j$ during time slot $k$ |
| $d_{i,j}$ | Distance of $SU_j$ from $D_{i}^{(j)}$ |
| $A$ | Fraction of time available for IoT devices for data transmission |
| $P_{u_{i},k}$ | Transmit power of $D_{i}^{(j)}$ during time slot $k$ |
| $P_0$ | Power of AWGN noise |
| $P_{u_{i},max}$ | Maximum transmit power of IoT devices |
| $\eta_{SIC}$ | Minimum SIC power difference |

The mathematical symbols and their physical interpretation in Table 1.

### A. CHANNEL MODEL

1) COMMUNICATION BETWEEN IoT DEVICES AND SU

Let $g_{i,j,k}$ represents the channel gain of communication between IoT device $D_{i}^{(j)}$ and sector UAV $SU_j$ during time slot $k, \forall i \in \mathcal{N}_j, j \in \mathcal{M}$, and $k \in \mathcal{K}$. Assuming that the communication between the SU and IoT devices suffers from both path loss and fading, the channel gain is given as

$$g_{i,j,k} = \frac{\beta_0 |h_{i,j,k}|^2}{d_{i,j}^2}$$

$$= \frac{\beta_0 |h_{i,j,k}|^2}{\left[(x_{SU_j} - x_i)^2 + (y_{SU_j} - y_i)^2 + h^2\right]}$$

where $\beta_0$ is the channel power gain at reference distance of 1 m, $h_{i,j,k}$ is the fading coefficient between device $D_{i}^{(j)}$ and sector UAV $SU_j$ during time slot $k$ and $d_{i,j} = \sqrt{(x_{SU_j} - x_i)^2 + (y_{SU_j} - y_i)^2 + h^2}$ is the distance of sector UAV $SU_j$ from the device $D_{i}^{(j)}$.

2) COMMUNICATION BETWEEN SU AND AU

During time frame $T_j$, $j \in \mathcal{M}$, the AU traverses through $j^{th}$ sector and collects data from the SU $SU_j$. Since, the AU moves
Then, the channel gain for the communication link between SU and the IoT nodes in IoT devices over the TDMA cycle. Assume that all the IoT nodes in SU can be used for uplink NOMA system, we assume that the IoT device SU receives the superimposed signal and apply successive interference cancellation (SIC) to decode the individual signals by following a predefined order. Though, any decoding order can be used for uplink NOMA system, we assume that the IoT devices are decoded in the decreasing order of their channel gain. So, for time slot $k$, if we assume the order of channel gains to be

$$g_{1,j,k} \geq g_{2,j,k} \geq \ldots \geq g_{i,j,k} \geq \ldots \geq g_{N_j,j,k},$$

then, the SU$_j$ decodes the signals in the following order: $D^{(1)}_j, D^{(2)}_j, \ldots, D^{(i)}_j, \ldots, D^{(N_j)}_j$. So, while decoding the signals, the IoT device $D^{(i)}_j$ will get interference because of the devices whose channel gains are lower than that of device $i$. Thus, the data rate achieved for device $D^{(i)}_j$ during time slot $k$ is

$$R_{i,j,k} = m \log_2 \left( 1 + \frac{P_{i,j,k} g_{i,j,k}}{I_{i,j,k} + N_0} \right), \quad \forall i \in N_j$$

where, the pre-log factor $m = (M - 1)/M$ indicates the fraction of time available for IoT devices for data transmission, $P_{i,j,k}$ is the transmitting power of $D^{(i)}_j$ during time slot $k$, $N_0$ is the power of AWGN noise and $I_{i,j,k}$ represents the intra-sector interference for device $i$, given as

$$I_{i,j,k} = \sum_{l=1}^{N_j} P_{l,j,k} g_{l,j,k}.$$  

It is important to notice that we are not using separate binary indicator to indicate device activation during a time slot, since it is reflected by the power, i.e., when $P_{i,j,k} = 0$, device $D^{(i)}_j$ is not transmitting during time slot $k$, and vice versa. Thus, the total data rate achieved at SU$_j$ during time slot $k$ is

$$R_{j,k} = \sum_{i=1}^{N_j} R_{i,j,k} = \sum_{i=1}^{N_j} m \log_2 \left( 1 + \frac{P_{i,j,k} g_{i,j,k}}{I_{i,j,k} + N_0} \right)$$

$$= m \log_2 \left( 1 + \frac{\sum_{i=1}^{N_j} P_{i,j,k} g_{i,j,k}}{N_0} \right), \quad k \in K, \quad j \notin T_j.$$  

However, for $k \in T_j$, i.e., during time frame $j$, the SU$_j$ will not receive any information from the respective IoT nodes, thus resulting $R_{j,k} = 0$. After joint decoding, the SU$_j$ stores all the data in the buffer. Thus, the total data collected at SU$_j$ over the TDMA cycle is

$$D_j = \sum_{k=1}^{K} R_{j,k} \tau$$

$$= \sum_{k=1}^{K} m \log_2 \left( 1 + \frac{\sum_{i=1}^{N_j} P_{i,j,k} g_{i,j,k}}{N_0} \right), \quad j \in M.$$  

As mentioned earlier, the data transmission from IoT devices to TBS is performed in two stages: (1) Data transmission from IoT devices to SU and (2) Data transmission from SU to TBS.

1) DATA TRANSMISSION FROM IoT DEVICES TO SU

Let us take the sector UAV SU$_j$ and its corresponding IoT node set $S_j$ as an example to analyze the data transmission between IoT devices and SU over the TDMA cycle. Assume that all the IoT nodes in $S_j$ are active nodes. For any time slot $k$, when $k \notin T_j$, all the $N_j$ nodes transmit their information to SU$_j$ by using NOMA, which is shown in Fig. 2. The SU$_j$ receives the superimposed signal and apply successive interference cancellation (SIC) to decode the individual signals by following a predefined order. Though, any decoding order can be used for uplink NOMA system, we assume that the IoT devices are decoded in the decreasing order of their channel gain. So, for time slot $k$, if we assume the order of channel gains to be

$$g_{1,j,k} \geq g_{2,j,k} \geq \ldots \geq g_{i,j,k} \geq \ldots \geq g_{N_j,j,k},$$

then, the SU$_j$ decodes the signals in the following order: $D^{(1)}_j, D^{(2)}_j, \ldots, D^{(i)}_j, \ldots, D^{(N_j)}_j$. So, while decoding the signals, the IoT device $D^{(i)}_j$ will get interference because of the devices whose channel gains are lower than that of device $i$. Thus, the data rate achieved for device $D^{(i)}_j$ during time slot $k$ is

$$R_{i,j,k} = m \log_2 \left( 1 + \frac{P_{i,j,k} g_{i,j,k}}{I_{i,j,k} + N_0} \right), \quad \forall i \in N_j$$

where, the pre-log factor $m = (M - 1)/M$ indicates the fraction of time available for IoT devices for data transmission, $P_{i,j,k}$ is the transmitting power of $D^{(i)}_j$ during time slot $k$, $N_0$ is the power of AWGN noise and $I_{i,j,k}$ represents the intra-sector interference for device $i$, given as

$$I_{i,j,k} = \sum_{l=1}^{N_j} P_{l,j,k} g_{l,j,k}.$$  

It is important to notice that we are not using separate binary indicator to indicate device activation during a time slot, since it is reflected by the power, i.e., when $P_{i,j,k} = 0$, device $D^{(i)}_j$ is not transmitting during time slot $k$, and vice versa. Thus, the total data rate achieved at SU$_j$ during time slot $k$ is

$$R_{j,k} = \sum_{i=1}^{N_j} R_{i,j,k} = \sum_{i=1}^{N_j} m \log_2 \left( 1 + \frac{P_{i,j,k} g_{i,j,k}}{I_{i,j,k} + N_0} \right)$$

$$= m \log_2 \left( 1 + \frac{\sum_{i=1}^{N_j} P_{i,j,k} g_{i,j,k}}{N_0} \right), \quad k \in K, \quad j \notin T_j.$$  

However, for $k \in T_j$, i.e., during time frame $j$, the SU$_j$ will not receive any information from the respective IoT nodes, thus resulting $R_{j,k} = 0$. After joint decoding, the SU$_j$ stores all the data in the buffer. Thus, the total data collected at SU$_j$ over the TDMA cycle is

$$D_j = \sum_{k=1}^{K} R_{j,k} \tau$$

$$= \sum_{k=1}^{K} m \log_2 \left( 1 + \frac{\sum_{i=1}^{N_j} P_{i,j,k} g_{i,j,k}}{N_0} \right), \quad j \in M.$$  

FIGURE 2. Time frame representation of data transmission from IoT devices to SU$_j$.

FIGURE 3. Time frame representation of data transmission from SU$_j$ to TBS.
where \( \tau \) indicates the duration of each time slot in the TDMA cycle.

2) DATA TRANSMISSION BETWEEN SU AND TBS
All the SUs transmit their information to the TBS via AU by employing cyclical TDMA. The scheduling of each SU over a TDMA cycle is shown in Fig. 3. During time frame \( T_j \), the AU collects data from \( SU_j \) and forwards it to the TBS. The \( SU_j \) re-encodes the stored data into a single code word, and then transmits to the AU at rate

\[
R_j = \sum_{k=1}^{K} \frac{m}{2L} \log_2 \left( 1 + \frac{\sum_{i=1}^{N_j} P_{i,j,k} g_{i,j,k}}{N_0} \right), \quad j \in \mathcal{M},
\]

(12)

For each time slot \( k \), \( k \in T_j \), the AU receives the data from \( SU_j \) during the first half of time slot and forwards it to the TBS during the next half of time slot. If we assume that both \( SU_j \) and AU transmit with a fixed power of \( P_{SU,j} \) and \( P_{AU} \) respectively, then the channel capacity for both AU-SU and AU-TBS channels during time slot \( k \) are given as

\[
C_{AU,SU}^{(k)} = \frac{1}{2M} \log_2 \left( 1 + \frac{P_{SU,j} g_{SU,AU}^{(k)}}{N_0} \right),
\]

(13) and

\[
C_{AU,TBS}^{(k)} = \frac{1}{2M} \log_2 \left( 1 + \frac{P_{AU} g_{AU,TBS}^{(k)}}{N_0} \right),
\]

(14)

We assume that the values of \( P_{SU,j} \) and \( P_{AU} \) are such that \( C_{AU,TBS}^{(k)} \geq C_{AU,SU}^{(k)} \) and \( C_{AU,SU}^{(k)} \geq R_j \). With this assumption, all the information transmitted from \( SU_j \) can be decoded successfully at the TBS. Then, the system’s sum rate can be expressed as

\[
R_{sum} = \sum_{j=1}^{M} R_j
\]

\[
= \frac{m}{2L} \sum_{j=1}^{M} \sum_{k=1}^{K} \log_2 \left( 1 + \frac{\sum_{i=1}^{N_j} P_{i,j,k} g_{i,j,k}}{N_0} \right)
\]

\[
= \frac{1}{2L} \sum_{k=1}^{K} \sum_{j=1}^{M} m \log_2 \left( 1 + \frac{\sum_{i=1}^{N_j} P_{i,j,k} g_{i,j,k}}{N_0} \right),
\]

(15)

where \( \sum_{j=1}^{M} m \log_2 \left( 1 + \frac{\sum_{i=1}^{N_j} P_{i,j,k} g_{i,j,k}}{N_0} \right) \) denotes the system data collection rate over time slot \( k \).

III. PROBLEM FORMULATION
We aim to maximize the sum rate of the UAV assisted uplink IoT system, by jointly optimizing the location of SUs and transmitting power of IoT devices. Thus, the sum rate maximization problem can be formulated as

\[
P1 : \max_{x_{SU,j},y_{SU,j},P_{j}} R_{sum}
\]

(16a)

s.t. \( \frac{P_{i,j,k} g_{i,j,k}}{N_0} \geq \eta_{SIC} \)

\( \forall i = 1, 2, \ldots, (N_j - 1), j \in \mathcal{M}, k \in \mathcal{K} \)

(16b)

\( P_{i,j,k} \leq P_{u,max} \)

\( \forall i \in N_j, j \in \mathcal{M}, k \in \mathcal{K} \)

(16c)

where \( x_{SU,j} \) and \( y_{SU,j} \) represent the x-position and y-position of \( SU_j \) respectively and \( P_j \in \mathbb{R}^{N_j \times K} \) denotes the power allocation matrix of sector \( j \). The constraint (16b) indicates the SIC condition required for decoding of signals where (16c) represents the transmit power constraints of IoT nodes. From (15), we can conclude that the overall sum rate can be maximized by maximizing the system data collection rate over each time slot. Therefore, for a particular time slot \( k \), the problem P1 can be written as

\[
P2 : \max_{x_{SU,j},y_{SU,j},P_{j,k}} \sum_{j=1}^{M} m \log_2 \left( 1 + \frac{\sum_{i=1}^{N_j} P_{i,j,k} g_{i,j,k}}{N_0} \right)
\]

(17a)

s.t. \( \frac{P_{i,j,k} g_{i,j,k}}{N_0} \geq \eta_{SIC} \)

\( \forall i = 1, 2, \ldots, (N_j - 1), j \in \mathcal{M}, k \in \mathcal{K} \)

(17b)

\( P_{i,j,k} \leq P_{u,max} \)

\( \forall i \in N_j, j \in \mathcal{M}, k \in \mathcal{K} \)

(17c)

where \( P_{j,k} = \{ P_{i,j,k}, \forall i \in N_j \} \) is the column vector of matrix \( P_j \), indicating the power allocation of IoT devices over sector \( j \) during time slot \( k \).

IV. NOMA BASED RESOURCE ALLOCATION FOR RATE MAXIMIZATION
The problem P2 is non-convex due to the coupling between the variables. The optimal power allocation of IoT devices vary with the channel gains and the channel gains explicitly depend upon the SU locations. Therefore, the problem is decoupled into two sub problems: 1) Placement of SUs; and 2) Power control of IoT devices. We first optimize the location of each sector UAV by minimizing the sum distances of SU from the respective IoT devices. Then, by considering the optimal UAV locations, we optimize the transmit power of IoT devices by applying Lagrange dual method. Note that for a given sectorization, maximizing the system data collection rate is equivalent to maximizing the data collection rate over each sector. This is because, the overall system data collection rate is the summation of data collection rates over all sectors, which are mutually independent. Therefore, we can further simplify the problem by solving P2 over each sector separately. Thus, for any sector \( j \), we can reformulate the problem P2 as

\[
P3 : \max_{x_{SU,j},y_{SU,j}} \sum_{i=1}^{N_j} \log_2 \left( 1 + \frac{P_{i,j,k} g_{i,j,k}}{N_0} \right)
\]

(18a)

s.t. \( \frac{P_{i,j,k} g_{i,j,k}}{N_0} \geq \eta_{SIC} \)

\( \forall i = 1, 2, \ldots, (N_j - 1) \)

(18b)

\( P_{i,j,k} \leq P_{u,max} \)

\( \forall i \in N_j \)

(18c)
A. PLACEMENT OPTIMIZATION OF SU
Given the location of IoT devices, we can optimize the position of SU in sector $j$ by solving the following problem:

$$
P4: \max_{x_{SUj}, y_{SUj}} m \log_2 \left( 1 + \frac{\sum_{i=1}^{N_j} \beta_0 |h_{i,j,k}|^2 d_{i,j}^{-2}}{N_0} \right), \tag{19}
$$

We have considered static IoT devices and UAV locations during a given time slot [3], [12], [24], [33]. Thereby, we assume LoS communication links [12], [24], [33], with negligible multipath fading effect [3].

The perfect channel state information (CSI) acquisition can be performed by mechanism given in [10], [34], [35]. Although the CSI estimation may not be perfect in time-varying environment, the effect of CSI error can be negotiable in nearly static block fading channel [10], [35]. Therefore, with fixed transmit power, the transmission rate only depends on the distance between the SU and the respective IoT devices. Thus, maximizing $P4$ is equivalent to minimizing the sum of distances of $SU$ and the respective IoT devices. Thus, maximizing $P4$ is equivalent to minimizing the sum of distances of $SU_j$ from all the respective IoT devices. To this end, the problem $P4$ can be further transformed as

$$
P5: \max_{x_{SUj}, y_{SUj}} \sum_{i=1}^{N_j} (x_{SUj} - x_i^{(j)})^2 + (y_{SUj} - y_i^{(j)})^2, \tag{20}
$$

The optimization problem (P5) is convex in nature and the optimal solution to this problem can be obtained by equating the first order derivative to zero, which can be expressed as

$$
2N_j x_{SUj} - 2 \sum_{i=1}^{N_j} x_i^{(j)} = 0, \tag{21}
$$

and

$$
2N_j y_{SUj} - 2 \sum_{i=1}^{N_j} y_i^{(j)} = 0. \tag{22}
$$

Solving (21) and (22), we obtain the optimal solution

$$
x_{SUj}^* = \frac{1}{N_j} \sum_{i=1}^{N_j} x_i^{(j)}, \text{ and } y_{SUj}^* = \frac{1}{N_j} \sum_{i=1}^{N_j} y_i^{(j)}. \tag{23}
$$

B. POWER CONTROL OF IoT DEVICES
In this section, we focus on developing an optimal solution for the power control of IoT devices over each sector in the NOMA based UAV assisted uplink IoT system. For any sector $j$, the power control problem is given as

$$
P6: \max_{P_{i,j,k}} m \log_2 \left( 1 + \frac{\sum_{i=1}^{N_j} P_{i,j,k} g_{i,j,k}}{N_0} \right), \tag{24}
$$

s.t. \hspace{1cm} \sum_{i=1}^{N_j} P_{i,j,k} g_{i,j,k} \geq \eta_{SIC}, \hspace{1cm} \forall i = 1, 2, \ldots, (N_j - 1)

$$
P_{i,j,k} \leq P_{u,max}, \hspace{0.5cm} \forall i = 1, 2, \ldots, N_j \tag{24}
$$

The above problem is convex and can be solved by using Lagrange dual method. The Lagrange function for the above problem can be written as

$$
\mathcal{L}(\lambda, \mu, P_{i,j,k}) = m \log_2 \left( 1 + \frac{\sum_{i=1}^{N_j} P_{i,j,k} g_{i,j,k}}{N_0} \right)
$$

$$
+ \lambda \left( P_{i,j,k} g_{i,j,k} - \eta_{SIC} \sum_{i=1}^{N_j} P_{i,j,k} g_{i,j,k} \right)
$$

$$
- \mu_i (P_{i,j,k} - P_{u,max}) \tag{25}
$$

where, $\lambda = \{\lambda_1, \lambda_2, \ldots, \lambda_{N_j-1}\}$ and $\mu = \{\mu_1, \mu_2, \ldots, \mu_{N_j}\}$ are the set of Lagrange multipliers. Then, the Lagrange dual function can be expressed as

$$
\mathcal{L}(\lambda, \mu) = \sup_{P_{i,j,k} \in \mathbb{R}_+} \mathcal{L}(\lambda, \mu, P_{i,j,k}) \tag{26}
$$

Since, (24) is a convex optimization problem, both the primal problem as well as the dual problem must satisfy the Karush-Kuhn-Tucker(KKT) conditions. Thus, by solving the KKT condition $\frac{\partial \mathcal{L}(\lambda, \mu)}{\partial P_{i,j,k}} = 0$, the optimal power allocation can be given as

$$
P_{i,j,k}^* = \begin{cases} 
\left[ \frac{m}{N_j} \sum_{i=1}^{N_j} P_{i,j,k} g_{i,j,k} \right]^{+}, \hspace{0.5cm} \text{if } i \neq N_j \\
\left[ \frac{m}{N_j} \sum_{i=1}^{N_j} P_{i,j,k} g_{i,j,k} \right]^{+}, \hspace{0.5cm} \text{if } i = N_j 
\end{cases} \tag{27}
$$

where $[x]^+$ can be defined as $[x]^+ = \max(x, 0)$. Note that $\mathcal{L}(\lambda, \mu)$ is not differentiable. Therefore, to find the optimal value of Lagrange multipliers, we use the subgradient method [33], where the Lagrange multipliers are updated as follows

$$
\lambda_i[n + 1] = \lambda_i[n] - \delta_i[n] \left( P_{i,j,k}[n] g_{i,j,k} - \eta_{SIC} \sum_{i=1}^{N_j} P_{i,j,k}[n] g_{i,j,k} \right) \tag{28}
$$

and

$$
\mu_i[n + 1] = \mu_i[n] - \delta_i[n] \left( P_{u,max} - P_{i,j,k}[n] \right) \tag{29}
$$

where $n$ and $\delta_i[n]$ represent the iteration step and step size respectively. The process of finding the optimal power allocation is presented in Algorithm 1. To elaborate, we first assign an initial feasible values to each of the $\lambda_i$ and $\mu_i$. Then, we optimize the $P_{i,j,k}, \forall i$, using Lagrange Dual.
method through an iterative approach, where in each iteration, we update the values of $\lambda_i$ and $\mu_i$ by using the previously obtained $P_{i,j,k}$. This process repeats until convergence. Note that for each sector, Algorithm 1 has to update a total of $(3N_j - 1)$ number of parameters. Thus, in worst case convergence, the Algorithm 1 has a complexity order of $O\left(K \sum_{j=1}^{M} (3N_j - 1)L_j\right)$, where $L_j$ is the maximum number of iteration required for convergence over sector $j$. However, with small $L_j$ value, Algorithm 1 shows fast computational performance.

Algorithm 1 NOMA Based Power Control Algorithm for Optimal IoT Transmit Power

| Input: | Channel gain of IoT devices |
|---|---|
| Output: | Transmit power of IoT devices |
| 1: | for $k \leftarrow 1$ to $K$ do |
| 2: | for $j \leftarrow 1$ to $M$ do |
| 3: | Initialize $\lambda_i[1] > 0$, $\mu_i[1] > 0$, $\delta_i[1] \leftarrow 1$, and $P_{i,j,k}[1] \leftarrow 0$, $\forall i \in N_j$. |
| 4: | Set $n \leftarrow 1$ |
| 5: | repeat |
| 6: | for $i \leftarrow 1$ to $N_j$ do |
| 7: | if $i \neq N_j$ then |
| 8: | Update $P_{i,j,k}[n]$ according to Eq. (27) |
| 9: | Update $\lambda_i[n+1]$ according to Eq. (28) |
| 10: | Update $\mu_i[n+1]$ according to Eq. (29) |
| 11: | else if $i = N_j$ then |
| 12: | Update $P_{i,j,k}[n]$ according to Eq. (27) |
| 13: | Update $\lambda_i[n+1]$ according to Eq. (28) |
| 14: | end if |
| 15: | end for |
| 16: | $n \leftarrow n + 1$ |
| 17: | $\delta_i[n] \leftarrow \frac{1}{n}$ |
| 18: | until $P_{i,j,k}$ converges |
| 19: | end for |
| 20: | end for |

V. PERFORMANCE EVALUATION

In this section, we evaluate the performance effectiveness of the proposed Cylindrical TDMA-NOMA scheme through extensive simulation results. The simulations are performed on MATLAB platform.

A. SIMULATION FRAMEWORK

We consider a circular disaster region of radius 500m. For simulation, we assume the IoT devices to be uniformly randomly distributed over the disaster region. A sample simulation scenario with 100 IoT devices is shown in Fig. 4, where the positions of IoT devices are marked by blue dots. The TBS is positioned at the center of the disaster region and is represented by green circle. The disaster region is divided into 10 sectors, i.e $M = 10$. For each sector, the horizontal location of SU is decided using Eq. (23) and is indicated by small square (marked with pink colour). The AU is flying on a circular trajectory of radius 300m, which is represented by the triangle symbol.

We assume that the central TBS has a coverage radius of 300m and the UAVs are flying at a constant height of 100m [18], [32]. The revolution period of AU is selected to be 80s, i.e, $T=80s$ [30]. The maximum uplink transmit power budget is set to be $P_{u,max} = 500mW$ [33]. Assuming the communication channels to be LOS, the system parameters are considered as $\theta_0 = 10^{-3}$ and $N_0 = 10^{-12}$Watts [31]. With this simulation scenario, we perform a Monte-Carlo simulation with 95% confidence interval by setting the minimum SIC power difference $\eta_{SIC} = 5$ dB [32].

B. SIMULATION RESULTS

First, we evaluate the convergence behaviour of the proposed iterative algorithm. For this, we fix the number of sectors $M = 10$, and the number of IoT devices $N = 60$. Fig. 5 shows the convergence behaviour of the proposed algorithm. We observe that as the iteration progresses, the system sum rate increases and converges to a value within four iterations. This concludes that the proposed algorithm is time-efficient and is suitable for UAV-based applications.

Fig. 6 shows the system sum rate variation with respect to the number of IoT nodes for different number of sectors.
We observe that as the number of IoT nodes increases, the node density for each sector increases, which in turn increases the system sum rate. On the other hand, a larger number of nodes causes more intra-sector interference which affects the rate of increase of system sum rate. Furthermore, Fig. 6 depicts that more number of sectors leads to higher sum rate. This is because increase in number of sectors results in decrease in the transmission distance between the SU and the respective IoT device, thus improves the transmission rate of each sector. It is also worth noting that the gap between the curves becomes more as we increase the number of IoT nodes. As the number of nodes increases, the node density decreases which eventually decreases the intra-sector interference and improves the transmission rate of each sector. This effect is more prominent for large number of IoT nodes.

Fig. 7 shows the impact of maximum uplink transmit power on the system sum rate. We fix the number of nodes \( N = 100 \) and analyze the system sum rate for different \( P_{u,max} \). It is noticed that the system sum rate increases with \( P_{u,max} \), which is fairly instinctive. However, as the maximum transmit power increases, the interference also increases. Therefore, for a given number of IoT nodes, we can achieve improved sum rate with lesser transmit power by increasing the number of sectors.

In Fig. 8, we analyze the performance of the proposed scheme with reference to the SU locations. For that we consider two scenarios; Cyclical TDMA-NOMA with optimal SU locations, Cyclical TDMA-NOMA with random SU locations. In this case, the number of sectors is taken as constant, i.e., \( M = 10 \). We observe that the optimal deployment results higher sum rate than the random deployment. At optimal SU location, the average distance between the SU and the IoT nodes is minimum, thus the average transmission rate of each sector is maximum, as explained in (23).

The simulation results presented so far consider the UAVs to operate at a fixed height of 100m. However, we have noticed that if we reduce the height to 80m, the system capacity improves by 5%, but the UAV coverage decreases by 35%. On the other hand, if we increase the height beyond 100m, the packet loss increases to an unacceptable level that is more than 4% [36]. Therefore, we fix the UAV height at 100m and evaluate the proposed scheme by comparing the performance results with other schemes.

Fig. 9 compares the proposed scheme, namely Cyclical TDMA-NOMA with two existing schemes — SS-FDNOMA [6] and Cyclical TDMA-OMA [22]. In SS-FDNOMA, SUs employ NOMA to access the IoT devices and the optimal power allocation is decided by using successive convex approximation (SCA) method. In case of Cyclical TDMA-OMA, which is a orthogonal multiple access (OMA) scheme, the SUs employ conventional TDMA method to
access ground IoT devices. Fig. 9a shows that when the number of IoT devices are less, the node density for each sector is also less, thus the chance of getting access is high which leads to high value of access percentage. However the NOMA schemes outperforms the OMA scheme due to their spectral efficiency. As the number of IoT devices increases, the node density for each sector also increases, which successively decreases the access percentage. The rate of decrease of system sum rate is high in the OMA scheme since each SU can access maximum one IoT device during each time slot of the TDMA cycle. In Fig. 9b, we compare the sum rate performance of different schemes with fixed number of sectors $M = 10$. We see that the proposed scheme outperforms the existing schemes in terms of system sum rate. In particular, the system sum rate increases by 8% and 22% when compared to SS-FDNOMA and Cyclical TDMA-OMA respectively.

VI. CONCLUSION

In this paper, we have proposed a novel relay based multi-UAV assisted communication system design to support uplink data transmission for IoT application during disaster scenario. Specifically, we have introduced a hybrid multiple access scheme, which integrates NOMA with cyclical TDMA to ensure reliable data transmission between IoT devices and the central server. The placement of UAVs and power allocation of IoT devices are jointly optimized to maximize the overall system capacity. From the extensive numerical simulations, we conclude that our proposed algorithm is converging with fewer number of iterations and can be applicable for real-time systems. Further, the percentage of serving IoT nodes using the proposed scheme is better than the existing schemes.

In the future, we plan to study the performance of UAV-assisted ultra-dense IoT network, in which the interference plays a key role in data transmission. Also, we intend to study the connectivity issues in multi-UAV system operating in terahertz (THz) frequency, which will act as a key enabler for 6G communication.

REFERENCES

[1] I. Lee and K. Lee, “The Internet of Things (IoT): Applications, investments, and challenges for enterprises,” Bus. Horizons, vol. 58, no. 4, pp. 431–440, Jul. 2015.
[2] R. K. Bishoyi and S. Misra, “Distributed resource allocation for collaborative data uploading in body-to-body networks,” IEEE Trans. Commun., vol. 70, no. 1, pp. 379–388, Jan. 2022.
[3] M. Liu, J. Yang, and G. Gui, “DSF-NOMA: UAV-assisted emergency communication technology in a heterogeneous Internet of Things,” IEEE Internet Things J., vol. 6, no. 3, pp. 5508–5519, Jun. 2019.
[4] N. L. Prasad, C. A. Ekbote, and B. Ramkumar, “Optimal deployment strategy for relay based UAV assisted cooperative communication for emergency applications,” in Proc. Nat. Conf. Commun. (NCC), Jul. 2021, pp. 1–6.
[5] K. Higuchi and A. Benjebbour, “Non-orthogonal multiple access (NOMA) with successive interference cancellation for future radio access,” IETE Trans. Commun., vol. 98, no. 3, pp. 403–414, 2015.
[6] M. Katwe, K. Singh, P. K. Sharma, C.-P. Li, and Z. Ding, “Dynamic user clustering and optimal power allocation in UAV-assisted full-duplex hybrid noma system,” IEEE Trans. Wireless Commun., early access, Sep. 24,2021, doi: 10.1109/TWC.2021.3113640.
[7] X. Pang, J. Tang, N. Zhao, X. Zhang, and Y. Qian, “Energy-efficient design for mmWave-enabled NOMA-UVNs networks,” Sci. China Inf. Sci., vol. 64, no. 4, pp. 1–14, Apr. 2021.
[8] N. Zhao, X. Pang, Z. Li, Y. Chen, F. Li, Z. Ding, and M.-S. Alouini, “Joint trajectory and precoding optimization for UAV-assisted NOMA networks,” IEEE Trans. Commun., vol. 67, no. 5, pp. 3723–3735, May 2019.
[9] M. Alzamad, A. El-Keyi, F. Lagum, and H. Yanikomeroglu, “3-D Placement of an unmanned aerial vehicle base station (UAV-BS) for energy-efficient maximal coverage,” IEEE Wireless Commun. Lett., vol. 6, no. 4, pp. 434–437, Aug. 2017.
[10] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, “Efficient deployment of multiple unmanned aerial vehicles for optimal wireless coverage,” IEEE Commun. Lett., vol. 20, no. 8, pp. 1647–1650, Jun. 2016.
[11] J. Lyu, Y. Zeng, R. Zhang, and T. J. Lim, “Placement optimization of UAV-mounted mobile base stations,” IEEE Commun. Lett., vol. 21, no. 3, pp. 604–607, Mar. 2017.
[12] Q. Wu, Y. Zeng, and R. Zhang, “Joint trajectory and communication design for multi-UAV enabled wireless networks,” IEEE Trans. Wireless Commun., vol. 17, no. 3, pp. 2109–2121, Mar. 2018.
[13] M. Ozuruk, J. P. B. Nadas, P. H. V. Klaine, S. Hissain, and M. A. Imran, “Clustering based UAV base station positioning for enhanced network capacity,” in Proc. Int. Conf. Adv. Emerg. Comput. Technol. (AEECT), Feb. 2020, pp. 1–6.
[14] L. Yang, H. Yao, J. Wang, C. Jiang, A. Benslimane, and Y. Liu, “Multi-UAV-enabled load-balance-mobile-edge computing for IoT networks,” IEEE Internet Things J., vol. 7, no. 8, pp. 6898–6908, Aug. 2020.
[15] J. Chen and D. Gesbert, “Optimal positioning of flying relays for wireless networks: A LOS map approach,” in Proc. IEEE Int. Conf. Commun. (ICC), May 2017, pp. 1–6.
[16] S. Zhang, H. Zhang, Q. He, K. Bian, and L. Song, “Joint trajectory and power optimization for UAV relay networks,” IEEE Commun. Lett., vol. 22, no. 1, pp. 161–164, Jan. 2018.
[17] Y. Chen, N. Zhao, Z. Ding, and M.-S. Alouini, “Multiple UAVs as relays: Multi-hop single link versus multiple dual-hop links,” IEEE Trans. Wireless Commun., vol. 17, no. 9, pp. 6348–6359, Sep. 2018.
[18] G. Zhang, H. Yan, Y. Zeng, M. Cui, and Y. Liu, “Trajectory optimization and power allocation for multi-hop UAV relaying communications,” IEEE Access, vol. 6, pp. 48566–48576, 2018.
[19] C. Zhan, Y. Zeng, and R. Zhang, “Energy-efficient data collection in UAV enabled wireless sensor network,” IEEE Wireless Commun. Lett., vol. 7, no. 3, pp. 328–331, Jun. 2018.
[20] D.-T. Ho, J. Park, and S. Shimamoto, “Performance evaluation of the PFSC based MAC protocol for WSN employing UAV in rician fading,” in Proc. IEEE Wireless Commun. Netw. Conf., Mar. 2011, pp. 55–60.
[21] R. Ma, R. Wang, G. Liu, H. Chen, and Z. Qin, “UAV-assisted data collection for ocean monitoring networks,” IEEE Netw., vol. 34, no. 6, pp. 250–258, Dec. 2020.
[22] C. Zhan and Y. Zeng, “Completion time minimization for Multi-UAV Enabled data collection,” IEEE Trans. Wireless Commun., vol. 18, no. 10, pp. 4859–4872, Oct. 2019.
[23] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, “Mobile unmanned aerial vehicles (UAVs) for energy-efficient Internet of Things communications,” IEEE Trans. Wireless Commun., vol. 16, no. 11, pp. 7574–7589, Nov. 2017.
[24] J. Wang, C. Jiang, Z. Wei, C. Pan, H. Zhang, and Y. Ren, “Joint UAV hovering altitude and power control for space-air-ground IoT networks,” IEEE Internet Things J., vol. 6, no. 2, pp. 1741–1753, Apr. 2019.
[25] M. S. Ali, H. Tabassum, and E. Hossain, “Dynamic user clustering and power allocation for uplink and downlink non-orthogonal multiple access (NOMA) systems,” IEEE Access, vol. 4, pp. 6325–6343, 2016.
[26] G. Tang, C. Lee, N. Kim, W. Kang, T.-V. Nguyen, and S. Cho, “Throughput maximization for uplink IoT NOMA systems with efficient resource allocation,” in Proc. Int. Conf. Inf. Commun. Technol. Converg. (ICTC), Oct. 2020, pp. 1763–1765.
[27] H. Zhang, B. Wang, C. Chen, X. Cheng, and H. Li, “Resource allocation in uav-noma communication systems based on proportional fairness,” J. Commun. Inf. Netw., vol. 5, no. 2, pp. 111–120, 2020.
[28] W. Feng, J. Tang, N. Zhao, Y. Fu, X. Zhang, K. Cumanan, and K.-K. Wong, “NOMA-based UAV-aided networks for emergency communications,” China Commun., vol. 17, no. 11, pp. 54–66, Nov. 2020.
[29] A. Masaracchia, L. D. Nguyen, T. Q. Duong, C. Yin, O. A. Dobre, and E. Garcia-Palacios, “Energy-efficient and throughput fair resource allocation for TS-NOMA UAV-assisted communications,” IEEE Trans. Commun., vol. 68, no. 11, pp. 7156–7169, Nov. 2020.
[30] J. Sun, Z. Wang, and Q. Huang, “Cyclical NOMA based UAV-enabled wireless network,” IEEE Access, vol. 7, pp. 4248–4259, 2018.

[31] Z. Hadzi-Velkov, S. Pejoski, N. Zlatanov, and R. Schober, “UAV-assisted wireless powered relay networks with cyclical NOMA-TDMA,” IEEE Wireless Commun. Lett., vol. 9, no. 12, pp. 2088–2092, Dec. 2020.

[32] W. Chen, S. Zhao, R. Zhang, Y. Chen, and L. Yang, “UAV-assisted data collection with nonorthogonal multiple access,” IEEE Internet Things J., vol. 8, no. 1, pp. 501–511, Jan. 2021.

[33] R. Duan, J. Wang, C. Jiang, H. Yao, Y. Ren, and Y. Qian, “Resource allocation for multi-UAV aided IoT NOMA uplink transmission systems,” IEEE Internet Things J., vol. 6, no. 4, pp. 7025–7037, Aug. 2019.

[34] L. Zhu, J. Zhang, Z. Xiao, X. Cao, X.-G. Xia, and R. Schober, “Millimeter-wave full-duplex UAV relay: Joint positioning, beamforming, and power control,” IEEE J. Sel. Areas Commun., vol. 38, no. 9, pp. 2057–2073, Sep. 2020.

[35] K. Wang, W. Liang, Y. Yuan, Y. Liu, Z. Ma, and Z. Ding, “User clustering and power allocation for hybrid non-orthogonal multiple access systems,” IEEE Trans. Veh. Technol., vol. 68, no. 12, pp. 12052–12065, Oct. 2019.

[36] N. Kumar, M. Ghosh, and C. Singhal, “UAV network for surveillance of inaccessible regions with zero blind spots,” in Proc. IEEE Conf. Comput. Commun. Workshops, Jul. 2020, pp. 1213–1218.

**SUBHRAJIT BARICK** received the B.Tech. degree in electronics and telecommunications engineering from the Biju Patnaik University of Technology (BPUT), India, in 2013, and the M.Tech. degree in communication engineering from the Indian Institute of Information Technology, Design and Manufacturing (IIITDM), India, in 2016. He is currently pursuing the Ph.D. degree with the Department of Electronics and Electrical Communication Engineering, IIT Kharagpur, India. His research interests include network resource management, UAV communication, and machine learning.

**CHEHTNA SINGHAL** (Senior Member, IEEE) received the B.Eng. degree in electronics and telecommunications from the University of Pune, India, in 2008, and the M.Tech. degree in computer technology and the Ph.D. degree from the Indian Institute of Technology (IIT) Delhi, in 2010 and 2015, respectively. She worked with the IBM Software Laboratory, New Delhi, as a Software Engineer, in 2010, for a year. She has been working as an Assistant Professor with the Department of Electronics and Electrical Communication Engineering, IIT Kharagpur, since 2015. Her research interests include next generation heterogeneous wireless networks, with emphasis on cross-layer optimization, adaptive multimedia services, energy efficiency, and resource allocation.

---

**SUBHRAJIT BARICK**

**CHEHTNA SINGHAL**