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Minimizing energy consumption for NOMA multi-drone communications in automotive-industry 5.0

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ABSTRACT

The forthcoming era of the automotive industry, known as Automotive-Industry 5.0, will leverage the latest advancements in 6G communications technology to enable reliable, computationally advanced, and energy-efficient exchange of data between diverse onboard sensors, drones and other vehicles. We propose a non-orthogonal multiple access (NOMA) multi-drone communications network in order to address the requirements of enormous connections, various quality of services (QoS), ultra-reliability, and low latency in upcoming sixth-generation (6G) drone communications. Through the use of a power optimization framework, one of our goals is to evaluate the energy efficiency of the system. In particular, we define a non-convex power optimization problem while considering the possibility of imperfect successive interference cancellation (SIC) detection. Therefore, the goal is to reduce the total energy consumption of NOMA drone communications while guaranteeing the lowest possible rate for wireless devices. We use a novel method based on iterative sequential quadratic programming (SQP) to get the best possible solution to the non-convex optimization problem so that we may move on to the next step and solve it. The standard OMA framework, the Karush–Kuhn–Tucker (KKT)-based NOMA framework, and the average power NOMA framework are compared with the newly proposed optimization framework. The results of the Monte Carlo simulation demonstrate the accuracy of our derivations. The results that have been presented also demonstrate that the optimization framework that has been proposed is superior to previous benchmark frameworks in terms of system-achievable energy efficiency.

1. Introduction

The Automotive-Industry 5.0 will prioritize the seamless interaction between humans and autonomous vehicles. This transformative phase of the automotive industry will leverage emerging technologies such as sixth-generation (6G) communications, artificial intelligence, and blockchain (Maddikunta et al., 2022; Mirza et al., 2023). In the automotive domain, Industry 5.0 will bolster the reliability of wireless connectivity, enable humans to collaborate with vehicles in sharing data, and foster the development of dependable autonomous driving applications (Khan et al., 2022c). Additionally, the Automotive-Industry 5.0 will concentrate on building an ecosystem for environmentally friendly transportation with minimal carbon dioxide emissions. 6G communications will play a vital role in the realization of Automotive-Industry 5.0 by offering robust and high-speed communications that can support the extensive data sharing between vehicle sensors and the cloud (Ahmed et al., 2022). Moreover, 6G will also facilitate energy-efficient green communications (Mahmood et al., 2022b).

Drone communications have the potential to play a significant role in 6G networks due to their capability to provide high mobility

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and fully autonomous operations (Azari et al., 2022). The ability to remotely control and monitor drones relies heavily on drone communication technology (Raja et al., 2022). The drone communicates with other devices, such as ground wireless devices, other drones, or satellites, to share data and information (Khan et al., 2022i). A direct radio frequency (RF) link is typically used for communication between a drone and a wireless device on the ground (Mahmood et al., 2020). Through this connection, the pilot can direct the drone's movements, make changes to its flight plan, and monitor the drone's altitude, speed, and GPS coordinates in real-time (Hassija et al., 2021). Sometimes, a satellite or long-range cellular connection can be used to allow a drone and a wireless device on the ground to communicate with each other. Thanks to this, the drone can be piloted from any location on Earth (Zarbakhsh and Sebak, 2022). As part of a larger drone system, drones are able to communicate with one another and coordinate their actions. A group of drones, for instance, could pool their resources to perform a comprehensive area scan, then analyze and draw conclusions from the data they collect collectively (Rasheed et al., 2022). Drone communication enables the transfer of data and images captured by the drone's sensors and cameras, in addition to control and coordination. In addition to monitoring and inspection, mapping and surveying are some of the many potential applications for this information (Jiang et al., 2022). The precision and dependability of the data collected by the drone are directly related to the quality of its communication system.

Recently, non-orthogonal multiple access (NOMA), along with other merging technologies, have gained significant attention due to their high-performance capability (Ahmed et al., 2023; Wahid et al., 2023). NOMA is a multiple-access approach that shows promise for use in 6G and beyond communication networks (Khan et al., 2022a). By allowing users to share the same frequency resources, NOMA improves spectrum efficiency and allows for larger data rates than conventional multiple-access methods (Khan et al., 2022b). Superposition coding is the foundation of the NOMA protocol. In NOMA, signals from different wireless devices are transmitted simultaneously because they share the same frequency resources (Vaezi et al., 2019). However, depending on the channel conditions, each device's signal is encoded with a unique transmitting power. Signals from many wireless devices are decoded at the receiver by first performing successive interference cancellation (SIC) (Basharat et al., 2022). In SIC, the strongest device's signal is decoded first, then subtracted from the overall signal, and the procedure is repeated for the weaker devices in descending order of their channel conditions (Maraqa et al., 2020). In contrast to traditional multiple access methods like orthogonal multiple access (OMA), NOMA effectively increases the number of wireless devices that can use the same frequency resources, resulting in greater spectral efficiency and better data rates (Dai et al., 2018; Khan et al., 2019).

When NOMA and drone communications are combined, it may be possible to increase the spectrum efficiency, dependability, network capacity, energy efficiency, and support for heterogeneous services of future 6G communication systems (Liu et al., 2019). More specifically, with NOMA, many drones can efficiently share the same frequency resources, leading to better data rates and greater spectrum efficiency (Khan et al., 2021a). This can be useful for resolving the problems caused by the scarcity of available frequency drone communication systems (Do et al., 2021a). Moreover, NOMA allows for more reliable drone communication systems by efficiently allocating resources to ground wireless devices based on channel circumstances (Liu et al., 2022). NOMA also improves network capacity by allowing numerous drones to share the same frequency resources, hence allowing for a greater number of wireless devices to be served (Khan et al., 2022d). Further, the energy efficiency of drone communication systems is enhanced by NOMA because of its ability to efficiently allocate resources, hence decreasing the amount of power required to transmit data (Shome et al., 2022). In addition, using NOMA, resources can be effectively divided up to meet the demands of a wide variety of drones and services. Moreover, the work in Pham et al. (2020) has proposed a visible light communication empowered NOMA drone communication to enhance the user's sum rate through resource optimization. Besides that, some other emerging technologies, such as intelligent reflecting surfaces (Khan et al., 2022e), backscatter communication (Khan et al., 2022f), mobile edge computing (Mahmood et al., 2022a), and intelligent transportation systems (Khan et al., 2022g), have recently also gained significant attention from researchers.

1.1. Recent advances

Recently, authors have integrated NOMA with drone communications. For example, Hou et al. (2019) have investigated the coverage probability in NOMA drone communications adopting stochastic geometry. Another work in Rupasinghe et al. (2019) has studied the outage sum rate performance in NOMA drone communications using NOMA beamforming with limited feedback. The authors of Hou et al. (2020) have proposed a new 3D NOMA drone communications network to investigate outage probability and ergodic capacity using stochastic geometry. Similarly, the work in Wang et al. (2019) has calculated the outage probability and sum capacity of the cooperative NOMA drone communications network. Tang et al. (2020) have studied physical layer security in cognitive radio-inspired NOMA drone communications through joint trajectory and power optimization. The research work in Chen et al. (2021) has maximized the sum rate of NOMA drone communications through efficient resource management. The article in Do et al. (2020) has investigated the outage probability of full-duplex NOMA drone communications. Feng et al. (2021) have provided a joint optimization framework to maximize the sum rate of millimetre wave-enabled NOMA drone communications. Furthermore, the paper in Abbasi et al. (2020) has studied the problem of coverage extension and sum rate maximization in new radio-enabled NOMA drone communications. The authors of Iradukunda et al. (2021) have optimized resource allocation to improve the worse user data rate in NOMA drone communications. The authors in Khan et al. (2023) have also proposed NOMA for non-terrestrial networks to improve the energy and spectral efficiency of LEO satellite.

In addition to the above literature, some researchers have also employed artificial intelligence algorithms for NOMA drone communications. In this regard, Pham et al. (2020) have proposed a joint optimization for sum rate maximization of NOMA drone communications exploiting Harris hawks optimization. The authors in Zhang et al. (2023) have adopted a deep reinforcement leaning for 3D drone placement and resource allocation problem to maximize the fair throughput of NOMA drone communications. Similarly, Zhong et al. (2022) have also maximized the system throughput of NOMA drone communications using multi-agent reinforcement learning. Khan et al. (2022h) have solved an optimization problem for efficient resource allocation using learning algorithm in NOMA vehicular networks. The article in Khairy et al. (2021) has proposed a constrained deep reinforcement learning approach for NOMA drone communications to improve energy consumption efficiency while maintaining the success probability of transmission. Moreover, the authors of Sharma et al. (2022) have employed multi-agent reinforcement learning to explore the energy consumption problem for NOMA drone communications. Cui et al. (2019) have adopted a machine learning algorithm to investigate the sum harvested power maximization problem in NOMA drone communications. Furthermore, Qian et al. (2022) have investigated a physical layer security problem for NOMA drone communications using deep reinforcement learning approach.

Of late, researchers have also studied the energy efficiency of NOMA drone communications. For instance, Khan et al. (2021a) have investigated energy efficiency for NOMA drone communications in automotive industry 5.0. The study in Masaracchia et al. (2020) has optimized power allocation for NOMA drone communications to maximize the energy efficiency of the system. Theses authors have further extended the work in Masaracchia et al. (2020) such that both energy efficiency and user fairness have combine optimized for NOMA drone communications (Masaracchia et al., 2020). Ihsan et al. (2023) have proposed a new optimization scheme for energy efficiency maximization in backscatter-aided NOMA vehicular communications. The research work in Jia et al. (2021) has considered NOMA and special modulation techniques for drone communications to maximize the energy efficiency through efficient power allocation. Moreover, the authors of AlJubayrin et al. (2022) have provided a joint optimization of power allocation and reflection coefficient for energy consumption efficiency in backscatter-aided NOMA drone communications. Asif et al. (2023) have investigated energy efficiency problem for backscatter-aided NOMA drone communications. Gupta et al. (2022) have proposed optimization problem for energy and spectral efficiency in NOMA drone communications using Balanced-grey wolf optimization approach. Do et al. (2021b) have considered energy harvesting approach for cooperative NOMA drone communications to investigate outage probability and ergodic capacity. Furthermore, Fu et al. (2023) have minimized the power consumption of drone communications through geometric programming optimization. In addition, the research work in Su et al. (2023) has presented an energy efficiency framework for device to device underlying NOMA drone communications.

1.2. Motivation and contributions

Based on the existing literature, various performance metrics have been investigated for NOMA drone communications networks. The reported performance metrics are sum rate maximization, outage probability, ergodic capacity, secrecy rate maximization, fairness and energy efficiency. It can be observed that the above research works have several shortcomings.

1. Most of the above works consider NOMA for single drone communications. In such systems, users associated with a drone can cause only NOMA interference to each other after SIC decoding process. These systems are simple and cannot be considered in practice.
2. Second, several works have considered NOMA in multi-drone communication; however, they do not study the energy efficiency of the system. They focus on other performance metrics.
3. Some works have also considered NOMA in multi-drone communications under the assumption of a perfect SIC decoding process. Please note that the SIC process is very important for practical NOMA implementation. However, decoding signal at the receiver side cannot always be done perfectly and there might be error during this process.
4. Guaranteeing SIC decoding at the receiver side is crucial for achieving high NOMA spectral and energy efficiency which requires additional constraint in the optimization framework. However, most of the proposed optimization framework don not consider this constraint.

Considering the above issues in the literature, it is important to design a more practical NOMA system. To do so, we consider a more practical optimization framework, where multi-drone communicate with their associated ground wireless devices using downlink NOMA protocol. More specifically, our optimization framework aims to reduce the system's total energy consumption under the assumption of imperfect SIC decoding. Our optimization framework also takes into account several practical constraints, i.e., the quality of services of all wireless devices, power difference among wireless devices for efficient SIC decoding, and total power control, respectively. The main contributions of this work can be summarized as follow.

- In this work, we consider a more practical optimization framework for NOMA drone communications. A multi-drone multi-cell communications scenario is considered where a drone in each cell communicate with associated ground wireless devices using downlink NOMA protocol. To enhance the spectral efficiency, the proposed system share same spectrum in all cells such that each drone cause co-channel interference to other drones in neighboring cells. Thus, we consider both co-channel interference and NOMA interference in our optimization framework. We also assume that SIC cannot always decode the wireless device signal perfectly. The objective of the proposed optimization framework is to reduce the total energy consumption of the system under imperfect SIC decoding process.
- The problem of energy consumption minimization is formulated under several practical constraints. In particular, we simultaneously optimize the transmit power of all drones while guaranteeing the minimum data rate of wireless devices. We also invoke an efficient SIC decoding constraint which ensure the minimum power gap among wireless devices over the same spectrum. The formulated energy consumption minimization problem is non-convex due to the co-channel and NOMA interference which is very hard to solve any traditional convex optimization methods. Therefore, we use a more efficient non-convex optimization method based on sequential quadratic programming to obtain the optimal solution.
- In addition to the proposed algorithm, we also consider some conventional algorithms for comparison. These algorithms are based on KKT conditions, average power NOMA and conventional OMA drone communications. The benefits of the proposed NOMA drone communication framework are demonstrated for drone available transmit power, the number of drones in the system, error during SIC decoding and the circuit power of the system. The numerical results show that our proposed optimization significantly improves energy consumption efficiency compared to other benchmark approaches.

The following structure can be used to organize the rest of our work: In Section 2, we will introduce the system model, various assumptions, and optimization problem. Section 3 will describe the different steps of our proposed optimization solution that aim to improve the sum rate of the system. Moving on to Section 4, we will present and analyze the numerical results based on Monte Carlo simulations. Finally, in Section 5, we will draw conclusions and suggest potential areas for further research.

2. System model of NOMA-enabled multi-drone communications

A transmission of multiple drones in the Automotive-Industry 5.0 is taken into consideration, as shown in Fig. 1. The downlink NOMA protocol is used by each drone in its coverage area to serve multiple wireless devices, whereas the OMA protocol is used among different drones. The group of drones is denoted by the notation $\{\mathcal{D} = d|1, 2, \ldots, D\}$, where d is the index of any given drone. Each drone flies in the air and uses the NOMA protocol to

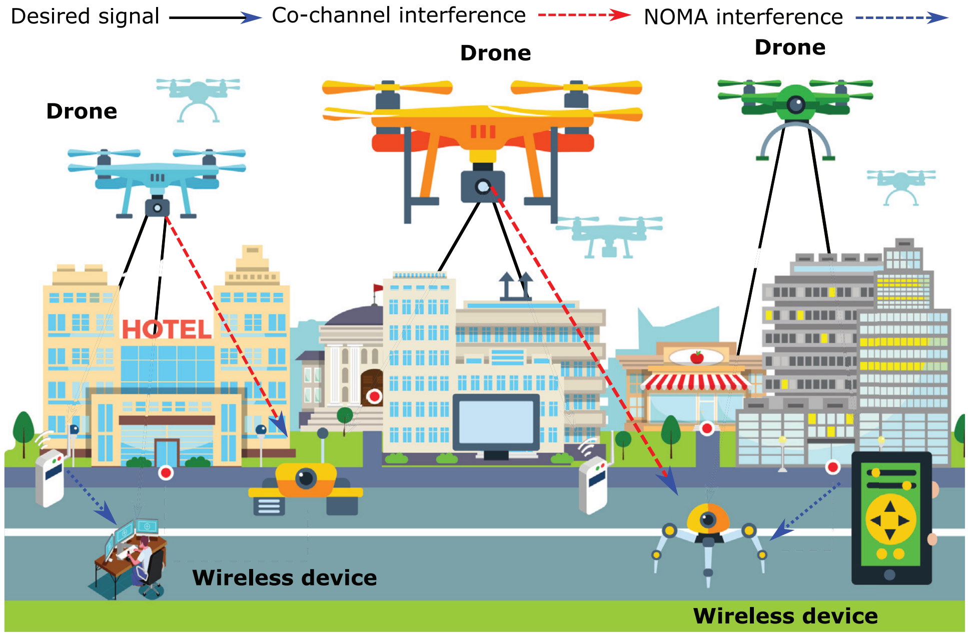

Fig. 1. System model of multi-drone NOMA communications in Automotive-Industry 5.0.

provide service to a group of wireless devices[1]. The group of wireless devices to which the d-th drone caters can be expressed mathematically as $\{\mathscr{U} = u|1, 2, \ldots, U\}$, where u represents the index of the particular wireless device being referred to. We assume in this work that the wireless devices' association with drones is complete prior to the proposed optimization framework. The effective wireless device association has the potential to substantially improve the functionality of the drone system; this aspect of the network's design has been set aside for further investigation. We make the following assumptions: All drones share the one spectrum resource in such a way that each drone receives co-channel interference from neighbouring drones; all devices in the network, including drones and wireless devices, are fitted with broadcast antennas; the channel state information (CSI) of all wireless devices is available at the drone; and the fast-fading channels are considered in this work, which undergoes Rician fading (Khan et al., 2020).

During the process of communication, each drone has the responsibility of simultaneously transmitting multiple pieces of information to its respective wireless devices using the same spectrum resource. In order to accomplish this, drones use the NOMA protocol to send a superimposed signal to the wireless devices that are associated with them. As a result, wireless devices that are associated with the same drone not only experience interference as a result of NOMA but also effected nearby drones as a result of co-channel, which is also referred to as inter-drone interference. Based on NOMA principle, wireless devices with low channel quality can be managed and removed by using the SIC decoding method on a wireless device with high channel quality. According to NOMA protocol, the superimposed signal of d-th drone for to its U wireless devices can be expressed as:

$$x_d = \sum_{u=1}^{U} \sqrt{p_{u,d}} x_{u,d}, \tag{1}$$

where x_d denotes the superimposed signal of n-th drone for wireless devices set U, where $p_{u,d}$ is the power allocation of d-th drone for u-th wireless device and $x_{u,d}$ is the data symbol of u-th wireless devices from d-th drone. When the drone is hovering at a moderate altitude, line-of-sight propagation dominates the channel in air-to-ground drone communication. This is because the drone is closer to the ground. According to a cartesian coordinate system that only has two dimensions, the wireless devices are believed to be situated in the horizontal plane at the point $\wp_u$, where $u \in U$ is. The following formula is used to determine the downlink channel gain from a d-th drone to a u-th wireless device:

$$H_{u,d} = \frac{\varrho_0}{||\ell - \wp_u||^2 + \Lambda} \tag{2}$$

where ϱ_0 is the reference channel gain per meter. Moreover, ℓ is the horizontal and vertical coordinate of d-th drone such as $\ell \in \{X_d, Y_d\}$. Further, Λ is the altitude of d-th drone. Considering both NOMA and co-channel interference, the received signal of u-th wireless devices from d-th drone can be written as:

$$y_{u,d} = H_{u,d}\left(\sqrt{p_{u,d}}x_{u,d} + \sum_{i=1}^{u-1}\sqrt{p_{i,d}}x_{i,d} + \delta\sum_{j=1}^{u+1}\sqrt{p_{j,d}}x_{j,d}\right) + \sum_{d'=1}^{D}H_{u,d}^{d'}\sum_{u'=1}^{U}\sqrt{p_{u',d'}}x_{u',d'} + \omega_{u,d}, \tag{3}$$

where the first part represents the desired signal of u-th wireless device from d-th drone, the second part is the NOMA interference after the SIC order, the third part is the interference due to the error in decoding process, where δ represents the SIC decoding error such that $\delta = \mathbb{E}[|x_{u,d} - \tilde{x}_{u,d}|^2]$ (Khan et al., 2021b). It is worth-mentioning here that $x_{u,d} - \tilde{x}_{u,d}$ shows the difference between the original signal and the signal with decoding error. Moreover, the fourth part is the co-channel interference from other drones and the last part is the additive white Gaussian noise with zero mean and σ^2 variance. Based on the received signal, the signal to interference plus noise ratio of u-th wireless device from d-th drone can be expressed as:

$$\gamma_{u,d} = \frac{p_{u,d}|H_{u,d}|^2}{\sigma^2 + |H_{u,d}|^2\left(\sum_{i=1}^{u-1}p_{i,d} + \Omega_{u,d}\right) + |H_{u,d}^{d'}|^2\Pi_{u,d}}. \tag{4}$$

where $\Omega_{u,d} = \delta\sum_{j=u+1}^{U}\sqrt{p_{j,d}}$ and $\Pi_{u,d} = \sum_{d'=1}^{D}H_{u,d}^{d'}\sum_{u'=1}^{U}\sqrt{p_{u',d'}}$, respectively. In order to ensure that the signal can be decoded, the NOMA protocol requires that the amount of power that is allotted on the

[1] In this work, we assume that the drones' fixed hover positions have already been calculated prior to power optimization. Optimal trajectory planning of drones can further improve the system performance and a hot topic to be investigated, however, is beyond the scope of this work.

d-th drone to the u-th wireless device be greater than the amount of power that is allotted on the $u-1$-th wireless device. Because SIC is so important to NOMA's performance, the power levels of wireless devices are a factor in determining whether or not it can be successfully implemented. The range and power of the drone's associated wireless devices should be sufficient to satisfy as

$$\left(p_{u,d} - \sum_{i=1}^{u-1} p_{i,d}\right)|H_{u-1}|^2 \geqslant \alpha, \ \forall d, \tag{5}$$

where α shows the power difference between two wireless devices which depends on the receiver sensitivity as well as the witless device channel conditions. Next we express the power consumption of d-th drone as:

$$P_d = \sum_{u=1}^{U} p_{u,d}, \tag{6}$$

Similarly, the total power consumption of the overall network can be described as:

$$P_{tot} = \sum_{d=1}^{D} p_d, \tag{7}$$

Now we define the data rate of u-th wireless device of d-th drone as:

$$R_{u,d} = \log_2(1+\gamma_{u,d}), \tag{8}$$

Accordingly, the sum rate of all wireless devices associated with d = th drone can be expressed as:

$$R_{sum} = \sum_{u=1}^{U} R_{u,d}, \tag{9}$$

Then the total rate of the overall network can be stated as:

$$R_{tot} = \sum_{d=1}^{D} R_{sum}, \tag{10}$$

The main goal of this study is to minimize the power consumption of a NOMA-enabled multi-drone communications network. Through power optimization, one of our primary goals is to simultaneously minimize the transmit power of each wireless device subject to its minimum data rate requirement. The optimization process for achieving the above objective can be mathematically formulated as a power minimization problem, which is given by

$$(\mathrm{P}): \quad \min_{p_{u,d}} P_{tot} \tag{11}$$

$$s.t. \ \sum_{d=1}^{D} R_{u,d} \geqslant R_{min}, \ \forall u, \tag{C-1}$$

$$\sum_{d=1}^{D} p_{u,d} \leqslant P_d, \ \forall u, \tag{C-2}$$

$$\sum_{d=1}^{D}\left(\sum_{i=1}^{u-1} p_{i,d} + \frac{\alpha}{|H_{u-1}|^2} \leqslant p_{u,d}\right), \ \forall u, \tag{C-3}$$

$$p_{u,d} \geqslant 0, \ \forall d, u, \tag{C-4}$$

where the objective function minimizes the total power consumption of NOMA multi-drone communications network. Constraint in (C-1) ensures the data rate requirements of all wireless devices. Constraint (C-2) limits the battery energy of all drones. Moreover, (C-3) makes the signal decoding process efficient while constraint (C-4) restricts all wireless devices to having positive power.

3. Proposed solution

Because the rate constraints make the optimization problem (P) non-convex, we use the SQP algorithm that provides the optimal solution for solving non-convex optimization problems. This allows us to optimize in a way that is more efficient. In this iterative algorithm, an original problem is broken down into a series of quadratic optimization sub-problems that can be solved individually. When using the SQP method, the first thing that needs to be done is to define a Jacobian matrix. For example,

$$J_d = \begin{bmatrix} \left[\frac{\partial R_{min}(p_{u,d})}{\partial p_{u,d}}\right]^T_{U\times U} \left[\frac{\partial P_d(p_{u,d})}{\partial p_{u,d}}\right]^T_{U\times U} \\ \left[\left[\frac{\partial \alpha_1(p_{u,d})}{\partial p_{u,d}}\right]^T_{U\times 1} \left[\frac{\partial \alpha_o(p_{u,d})}{\partial p_{u,d}}\right]^T_{U\times(U-1)}\right]^T_{U\times U} \end{bmatrix}^T, \forall d, \tag{12}$$

where

$$\begin{aligned} R_{min}(p_{u,d}) = {} & [R_{min} - R_{1,d}, R_{min} - R_{2,d}, \\ & \ldots, R_{min} - R_{u,d}, \ldots, R_{min} - R_{U,d}]^T, \end{aligned} \tag{13}$$

$$\begin{aligned} \alpha(p_{u,d}) = {} & \Bigg[0, p_{1,d} + \tfrac{\alpha}{|H_{1,d}|^2} - p_{2,d}, \\ & \ldots, \sum_{i=1}^{u-1} p_{i,d} + \tfrac{\alpha}{|H_{u-1}|^2} \leqslant p_{u,d}\Bigg]^T, \end{aligned} \tag{14}$$

$$P_d(p_{u,d}) = [p_{1,d} - P_d, p_{2,d} - P_d, \ldots, p_{U,d} - P_d]^T, \tag{15}$$

After performing the necessary calculations to derive (13) in part, the answer can be expressed as:

$$\frac{\partial R_{min}(p_{u,d})}{\partial p_{u,d}} = \begin{cases} \Psi_1, & \text{if } \ l = m, \\ \Psi_2, & \text{if } l > m, \\ 0, & \text{if } l < m, \end{cases} \tag{16}$$

where l and m represent the rows and columns of the matrix (16). In addition to this, the values of $\Psi1$ and $\Psi2$ are expressed depicted in (17) and (18).

$$\Psi_1 = \frac{-|H_{u,d}|^2}{(\sigma^2 + |H_{u,d}|^2 \sum_{i=1}^{u-1} p_{i,d}) + p_{u,d}|H_{u,d}|^2 + |H_{u,d}|^2 \Omega_{u,d} + |H^{d'}_{u,d}|^2 \Pi_{u,d}}, \tag{17}$$

$$\Psi_2 = \frac{p_{e,d}|H_{e,d}|^4}{(\sigma^2 + |H_{e,d}|^2 \sum_{i=1}^{u-1} p_{i,d})((\sigma^2 + |H_{e,d}|^2 \sum_{i=1}^{u-1} p_{i,d}) + p_{e,d}|H_{e,d}|^2) + |H_{e,d}|^2 \Omega_{e,d} + |H^{d'}_{e,d}|^2 \Pi_{e,d}}, \tag{18}$$

Accordingly, the value of (14) and (15) can be expressed as:

$$\frac{\partial P_d(p_{u,d})}{\partial p_{u,d}} = \begin{cases} 0, & \text{if } l > m, \\ 1, & \text{if } l = m, \\ 0, & \text{if } l < m, \end{cases} \tag{19}$$

$$\frac{\partial \alpha_1(p_{u,d})}{\partial p_{u,d}} = [0, 0, \dots, 0]^T, \ \forall u \in U, \tag{20}$$

and $\forall o > 1$ can be written as:

$$\frac{\partial \alpha_o(p_{u,d})}{\partial p_{u,d}} = \begin{cases} 1, & \text{if } l > m, \\ -1, & \text{if } l = m,. \\ 0, & \text{if } l < m, \end{cases} \tag{21}$$

After that, we move on to the computation of the Hessian matrix, for which we first define the Lagrangian function of the problem (P) as:

$$\begin{aligned} L(p_{u,d}, \lambda_{u,d}, \upsilon_{u,d}, \pi_{u,d}) &= \sum_{d=1}^{D}\sum_{u=1}^{U} p_{u,d} + \sum_{d=1}^{D}\sum_{u=1}^{U} \lambda_{u,d} \\ (R_{min} - R_{u,d}) &+ \sum_{d=1}^{D} \upsilon_{u,d}\left(\sum_{i=1}^{u-1} p_{i,d} + \tfrac{\omega}{|H_{u-1}|^2} - p_{u,d}\right) \\ &+ \sum_{d=1}^{D}\sum_{u=1}^{U} \pi_{u,d}(p_{u,d} - P_d), \end{aligned} \tag{22}$$

where $\lambda_{u,d}, \upsilon_{u,d}$ and $\pi_{u,d}$ denote the positive multipliers. Now we compute the Hessian matrix where l and m entries are stated as:

$$B = \begin{bmatrix} \frac{\partial^2 L(.)}{\partial^2 p_{1,d}} & \frac{\partial^2 L(.)}{\partial p_{1,d}\partial p_{2,d}} & \cdots & \frac{\partial^2 L(.)}{\partial p_{1,d}\partial p_{U,d}} \\ \frac{\partial^2 L(.)}{\partial p_{2,d}\partial p_{1,d}} & \frac{\partial^2 L(.)}{\partial^2 p_{2,d}} & \cdots & \frac{\partial^2 L(.)}{\partial p_{2,d}\partial p_{U,d}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 L(.)}{\partial p_{U,d}\partial p_{1,d}} & \frac{\partial^2 L(.)}{\partial p_{U,d}\partial p_{2,d}} & \cdots & \frac{\partial^2 L(.)}{\partial^2 p_{U,d}} \end{bmatrix}_{U \times U}, \tag{23}$$

where the partial derivatives of l and m entries can be expressed as:

$$H = \begin{cases} \Psi_3, & \text{if } \ l \geqslant m, \\ \Psi_4, & \text{if } l < m, \end{cases} \tag{24}$$

with the value of Ψ_3 is

$$\Psi_3 = \frac{|H_{u,d}|^4}{(\Phi^{(1)}_{u,d})^2} - \sum_{i=1}^{u-1} \frac{\Phi^{(2)}_{i,d}}{(\Phi^{(3)}_{i,d})^2} - \sum_{d=1}^{D}\sum_{u'=1}^{U} \frac{\Phi^{(4)}_{u',d'}}{(\Phi^{(5)}_{u',d'})^2}, \tag{25}$$

and the value of Ψ_4 is

$$\Psi_4 = \frac{\Phi^{(2)}_{f,d}}{(\Phi^{(3)}_{f,d})^2} - \sum_{f=1}^{i-1} \frac{\Phi^{(2)}_{f,d}}{(\Phi^{(3)}_{f,d})^2} - \sum_{d'=1}^{D}\sum_{f'=1}^{U} \frac{(\Phi^{(4)}_{f',d'})^2}{(\Phi^{(5)}_{f',d'})^2}. \tag{26}$$

The values of $\Phi^{(1)}_{u,d}, \Phi^{(2)}_{i,d}, \Phi^{(4)}_{i',d'}, \Phi^{(3)}_{f,d}$, and $\Phi^{(5)}_{f',d'}$ are further defined as:

$$\begin{aligned} \Phi^{(1)}_{u,d} = |H_{u,d}|^2 \sum_{i=1}^{u-1} p_{i,d} + \sigma^2 + p_{u,d}|H_{u,d}|^2 \\ + |H_{u,d}|^2\Omega_{u,d} + |H^{d'}_{u,d}|^2\Pi_{u,d}, \end{aligned} \tag{27}$$

$$\begin{aligned} \Phi^{(2)}_{i,d} = 2p_{i,d}|H_{i,d}|^4(2(|H_{i,d}|^2 \sum_{q=1}^{i-1} p_{q,d} + H^{d'}_{i,d}\Pi_{i,d}) \\ (2|H_{i,d}|^2) + 2p_{i,d}|H_{i,d}|^4 + |H_{i,d}|\Omega_{i,d}), \end{aligned} \tag{28}$$

$$\begin{aligned} \Phi^{(3)}_{f,d} &= \left(|H_{f,d}|^2 \sum_{s=1}^{f-1} p_{s,d} + |H_{f,d}|^2\Omega_{f,d} + |H^{d'}_{f,d}|^2\Pi_{f,d}\right)^2 \\ &\times\left(|H_{f,d}|^2 \sum_{s=1}^{f-1} p_{s,d} + |H_{f,d}|^2\Omega_{f,d} + |H^{d'}_{f,d}|^2\Pi_{f,d}\right) \\ &\times p_{f,d}|H_{f,d}|^2, \end{aligned} \tag{29}$$

$$\begin{aligned} \Phi^{(4)}_{i',d'} = p_{i',d'}|H_{i',d'}|^4(2(|H_{i',d'}|^2 \sum_{q'=1}^{i'-1} p_{q',d'} + |H^{d''}_{q',d'}|^2\Omega_{q',d'}) \\ \times(|H_{q',d'}|^2) + p_{q',d'}|H_{q',d'}|^2 + \Pi_{i',d'}), \end{aligned} \tag{30}$$

$$\begin{aligned} \Phi^{(5)}_{f',d'} &= \left(|H_{f',d'}|^2 \sum_{s'=1}^{f'-1} p_{s',d'} + |H_{f',d'}|^2\Omega_{f',d'}\right. \\ &\left. + |H^{d''}_{s',d'}|^2\Pi_{f',d'}\right)^2 + \left(|H_{f',d'}|^2 \sum_{s'=1}^{f'-1} p_{s',d'}\right. \\ &\left. + |H_{f',d'}|^2\Omega_{f',d'} + |H^{d''}_{f',d'}|^2\Pi_{f',d'}\right) p_{f',d}|H_{f',d'}|^2. \end{aligned} \tag{31}$$

After computing Jacobian and Hessian matrices, now we define matrix B as:

$$B = \begin{bmatrix} [H]_{U\times U}[J]^T_{U\times 3U} \\ [J]_{3U\times U}[0]_{3U\times 3U} \end{bmatrix}_{4U\times 4U}, \tag{32}$$

Next we iteratively update the estimate of $(p_{u,d}, \lambda_{u,d}, \upsilon_{u,d}, \pi_{u,d})$ as:

$$\begin{bmatrix} p^{t+1} \\ \lambda^{t+1} \\ \upsilon^{t+1} \\ \pi^{t+1} \end{bmatrix} = \begin{bmatrix} p^t + \theta\Xi^t_p \\ \lambda^t + \theta\Xi^t_\lambda \\ \upsilon^t + \theta\Xi^t_\upsilon \\ \pi^t + \theta\Xi^t_\pi \end{bmatrix} \tag{33}$$

where θ is the step size and Ξ denotes the correction vector which can be computed as:

$$\Xi = \left[\varphi L(p)^T, \varphi L(\lambda)^T, \varphi L(\upsilon)^T, \varphi L(\pi)^T\right]^T \varphi - B^{-1}, \tag{34}$$

where $\varphi L(p), \varphi L(\lambda), \varphi L(\upsilon)$, and $\varphi L(\pi)$ are the Gradients. Note that these gradients are obtained from the Lagrangian function which can be described as:

$$\varphi L(p_{u,d}) = -(1 + \lambda_{u,d})\Psi_5 + \sum_{i=1}^{u1} \lambda_{i,d}\Psi_6 - \upsilon_{u,d} + \pi_{u,d}, \tag{35}$$

$$\varphi L(\lambda_{u,d}) = \sum_{d=1}^{D}(R_{min} - R_{u,d}), \ \forall u, \tag{36}$$

$$\varphi L(\upsilon_{u,d}) = \sum_{d=1}^{D}\left(\sum_{i=1}^{u-1} p_{i,d} + \frac{\alpha}{|H_{u-1}|^2} - p_{u,d}\right), \ \forall u, \tag{37}$$

$$\varphi L(\pi_{u,d}) = \sum_{d=1}^{D}(p_{u,d} - P_d), \ \forall u, \tag{38}$$

where the values of Ψ_5 and Ψ_6 are described in (39) and (40).

$$\Psi_5 = \frac{|H_{u,d}|^2}{(\sigma^2 + |H_{u,d}|^2 \sum_{i=1}^{u-1} p_{i,d}) + p_{u,d}|H_{u,d}|^2 + |H_{u,d}|^2 \Omega_{u,d} + |H^{d'}_{u,d}|^2 \Pi_{u,d}}, \tag{39}$$

$$\Psi_6 = \frac{p_{j,d}|H_{j,d}|^4}{(\sigma^2 + |H_{j,d}|^2 \sum_{k=1}^{u-1} p_{k,d})((\sigma^2 + |H_{j,d}|^2 \sum_{k=1}^{u-1} p_{k,d}) + p_{j,d}|H_{j,d}|^2) + |H_{j,d}|^2 \Omega_{j,d} + |H^{d'}_{j,d}|^2 \Pi_{j,d}}. \tag{40}$$

In terms of iteration, the computational complexity of solving the proposed NOMA-enabled multi-drone communications framework using the SQP method is dependent on both D and U values. If T is the number of iterations required to achieve convergence, then the total computational complexity of the proposed framework can be expressed mathematically as $\mathcal{O}\{T(2DU)\}$.

4. Numerical results and discussion

In this section, we present and discuss the simulation results. For the simulations, we have taken variance as $\sigma^2 = 0.01$, the minimum data rate of wireless devices as $R_{min} = 1$ bps/Hz, transmit power of drone as $P_d = 30$ dBm, SIC decoding error parameter as $\delta = 0.1$, altitude of a drone as $\Lambda = 80$ m, the number of drones $D = 5$, and the number of wireless devices per drone as $U = 2$, until specified otherwise. We compare four systems where optimal NOMA drone communication refers to the proposed optimization approach provided in Section 3. Then, the sub-optimal NOMA drone communication is the system with the KKT approach, while average power NOMA drone communication represents a system with a fixed power allocation approach. In addition, conventional OMA drone communication describes the system where each drone can accommodate only one user at any time.

The significance of the transmitting power of the drone, as it relates to the power consumption efficiency of the system, is discussed in reference figure Fig. 2. The result shows that as the available battery power of drones increases, the power consumption efficiency of all optimization approaches declines. Additionally, it can be observed that the power consumption efficiency of the proposed approach and other approaches exhibits a bell-shaped curve. This curve shows that the power consumption efficiency first rises as the available battery power of the drone increases up to a point where it is at its maximum, and then it begins to fall and decrease as the available battery power continues to increase. On the other hand, the performance of the optimal NOMA drone communications approach that was proposed is significantly higher than that of other approaches. When the drone system is operating at a transmit power of over 10 dBm, for instance, the power consumption efficiency of the proposed optimal NOMA drone communications approach is 14.34 bpj/Hz, whereas the power consumption efficiency of sub-optimal NOMA drone communications, and other two benchmark drone communications is only 12.69, 11.53, and 8.46 bpj/Hz, respectively. It is worth noting that the performance gap between NOMA approaches and the OMA approach is significant, indicating that the OMA approach has subpar performance.

Next, we will discuss the significance of the total number of drones in terms of the system's overall efficiency regarding the consumption of power. In this regard, the power consumption efficiency is plotted when the total number of drones increases, which

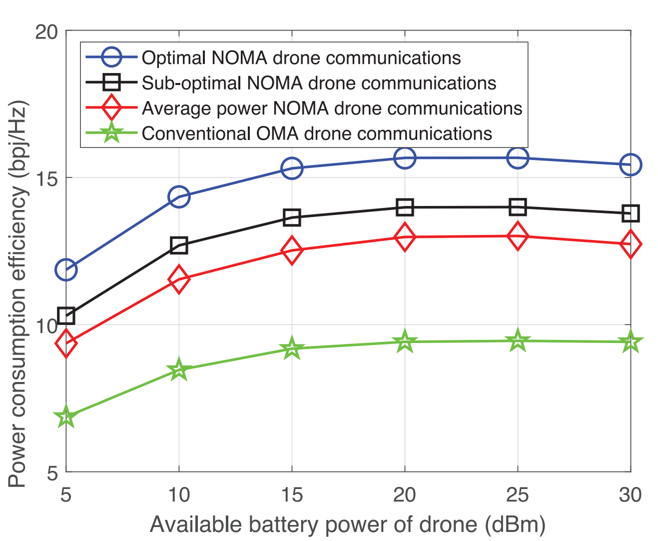

Fig. 2. Impact of available battery power on the power consumption efficiency of drone communications.

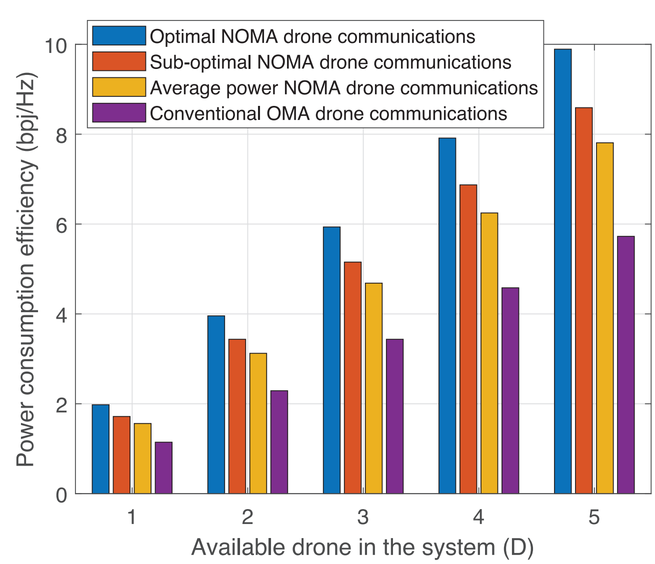

Fig. 3. Increasing number of drones versus power consumption efficiency of the system.

ranges from 1 to 5 in Fig. 3 When there are more drones in a system, the overall efficiency of power consumption across all optimization strategies is seen to improve. This is something that can be observed. On the other hand, in comparison to other optimization strategies, the optimal NOMA drone communications approach proposed here achieves a higher level of power consumption efficiency. For instance, when the number of drones reaches five, the power consumption efficiency of the optimal NOMA drone communications approach proposed is 9.89 bpj/Hz. At the same time, the power consumption efficiency of the other NOMA and OMA approaches to drone communications is 8.58, 7.80, and 5.72 bpj/Hz, respectively. The increasing power consumption efficiency gap between our proposed drone optimization scheme and other optimization schemes with an increase in the number of drones indicates the effectiveness of our approach for large-scale networks.

In this part of the research, we investigate how the performance of various optimization strategies is affected by the signal decoding error caused by SIC. The efficiency of power consumption is depicted in reference figure Fig. 3, which compares this metric to an increase in the value of the SIC decoding error, which can range anywhere from 0.1 to 0.5. It should come as no surprise that the power consumption efficiency of all drone communications approaches will suffer whenever there is an increase in the values of signal decoding errors brought on by an imperfect SIC. This demonstrates how crucial accurate SIC decoding is to the operation of practical NOMA systems. The optimal NOMA drone communications approach that has been proposed still achieves a higher overall power consumption efficiency than the other NOMA drone communications approaches. It is important to point out that the performance of the traditional OMA drone communications approach has not changed over time because OMA does not use SIC to decode signals. This is one of the reasons why this is important to note. For the sake of simplicity, the OMA result is not included in this discussion. The reason for this is that the OMA drone communication is unaffected by the fact that the SIC parameter values are not perfect (see Fig. 4).

Last but not least, reference figure Fig. 5 presents a discussion of the drone's circuit energy consumption on the total energy consumption of the system. This figure plots the power consumption efficiency versus the different values of circuit energy consumption of drone communications. When the circuit power is increased, we can observe that the power consumption efficiency of the optimal NOMA proposed for drone communications drops. When compared to the NOMA drone communications approaches, it would appear that the conventional OMA drone communications approach requires a significant amount of power for efficient transmission, which leads to a rapid reduction in power efficiency. A high level of energy efficiency can be achieved for a large scale of power-constrained wireless devices using the optimal NOMA drone communications approach that was proposed. Overall, we note that the proposed optimal NOMA drone communications using SQP approach provides very high power consumption efficiency for all system variables.

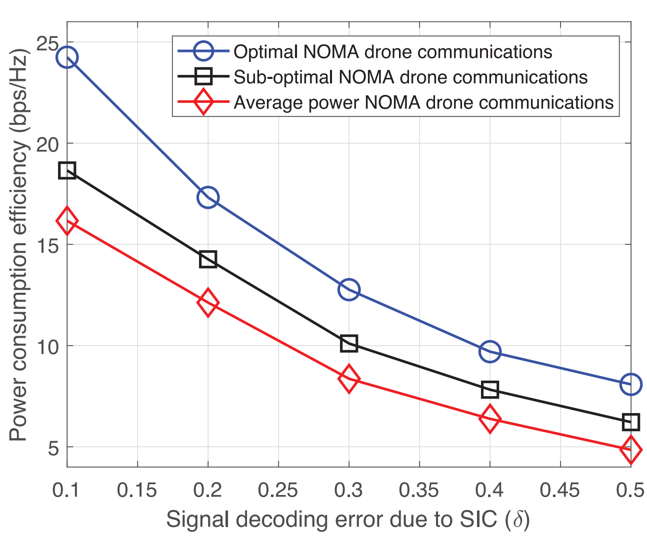

Fig. 4. Impact of signal decoding error on the power consumption efficiency of NOMA drone communications.

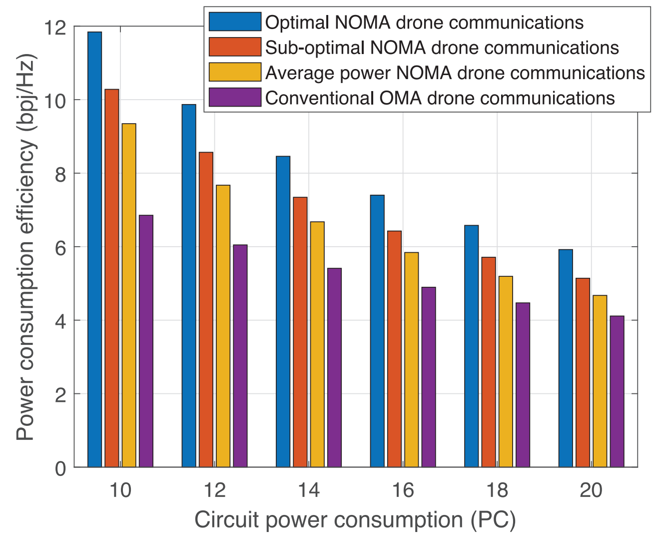

Fig. 5. Impact of circuit power consumption on the power consumption efficiency of drone communications.

5. Conclusion

NOMA and drones are the main drivers enabling low-powered, large-scale 6G communication networks. A new optimization framework for maximizing power consumption efficiency while accounting for signal decoding errors has been presented in this paper. In particular, the power allocation of drones has been minimized while simultaneously guaranteeing the lowest possible rate for all wireless devices. The high complexity energy consumption optimization problem has been successfully solved by utilizing a new iterative algorithm that is based on SQP. The results that have been presented demonstrate that the optimal NOMA drone communications system that was proposed in this work achieves high efficiency compared to other drone communications with regard to the amount of power that is consumed by the system. The optimization framework that was proposed is extensible in a number of different ways. For instance, it could be improved by factoring in the estimation errors associated with the channels. After that, it is also possible to extend it by incorporating backscatter communications and intelligent reflecting surfaces in the model of the system that was considered to further enhance the performance. These fascinating, unsolved issues can be investigated further in our upcoming research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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