Transmit or Backscatter: Communication Mode Selection for Narrowband IoT Systems

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***Abstract*—Backscatter communication is an energy-efficient communication technique for the Internet of things (IoT) devices. It enables data transmission by reflecting the incident radio signals. In this paper, we propose a communication mode selection scheme for IoT devices that can communicate using either active transmission or backscattering. In the active transmission mode, the IoT devices can transmit data over narrowband subcarriers using power-domain non-orthogonal multiple access (NOMA). In the backscattering mode, which operates over shorter distance than active transmission, nearby user equipment (UE) devices are used as relays. The UEs receive the backscattered signals from the IoT devices and forward them to the base station. We formulate a connection density maximization problem to select the communication mode used by each IoT device. We determine the IoT device pairing for active transmission mode with NOMA and UE-IoT device association for backscattering mode. The formulated problem is a binary integer programming problem. Although it can be solved optimally, the optimal algorithm incurs exponential computational complexity. Hence, we propose a low-complexity suboptimal algorithm to solve this problem. Results show that our proposed algorithm can enhance the connection density of narrowband IoT systems by up to 64% when compared with using single communication mode.**

***Index Terms*: Backscatter communications, non-orthogonal multiple access (NOMA), relaying.**

I. Introduction

The Internet of things (IoT) is an emerging paradigm in which IoT devices can support a wide variety of applications, such as home automation, healthcare, environmental monitoring, and industrial automation [2]. Due to its ubiquitous coverage, fifth generation (5G) and beyond 5G (B5G) wireless cellular networks are strong candidates for enabling the IoT, especially the massive IoT (mIoT) use case [3]. mIoT is characterized by a large number of low-cost low-power IoT devices (up to 10^6 devices per km^2) which can perform delay-tolerant tasks with relaxed latency requirements in the order of seconds or hours [4]. Due to the inconvenience of battery replacement and recharging in many IoT applications, the IoT devices are required to maintain a long battery lifetime which necessitates energy-efficient communication [5].

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Backscatter communication [6] is a promising energy-efficient communication technology for the IoT devices. The IoT devices reflect or backscatter an external excitation signal (e.g., power beacon) by tuning a set of antenna impedances. Subsequently, the frequency, phase, or amplitude of the excitation signal is modulated according to the data of these IoT devices. Backscatter communication enables the IoT devices to transmit their data without active transmission of radio frequency (RF) signals, which results in lower energy consumption [7]. Furthermore, low-power backscatter transmitters and receivers can be implemented with low cost [8].

In general, there are three types of backscatter communication systems, namely monostatic backscatter communication, bistatic backscatter communication, and ambient backscatter communication. In monostatic backscatter communication, the backscattering device (i.e., IoT device) modulates and reflects a dedicated excitation signal that is transmitted by the intended receiver of the data. On the other hand, in bistatic backscatter communication, the IoT device modulates and reflects a dedicated high-power excitation signal from an RF source which is different from the intended receiver (e.g., a base station (BS) or a TV tower). Bistatic backscatter communication is more reliable than monostatic backscatter communication since it involves the usage of a dedicated RF source that can generate a high power excitation signal. In addition, bistatic backscatter communication can operate over a longer communication range. In ambient backscatter communication, the dedicated high power excitation signal is replaced by an RF data signal that is intended for other devices, such as user equipment (UE) devices. Hence, ambient backscatter communication does not require the generation of dedicated excitation signals. For example, the downlink data signals, that are intended for UEs, can be beamformed by the BS to enhance the performance of an ambient backscatter communication system for IoT devices [9]. However, ambient backscatter communication entails the dependence on unpredictable data traffic to provide the required excitation signal for the IoT devices that use backscattering.

The performance of backscatter communication systems can be enhanced by relaying [1]. Relaying enables the receiver to obtain multiple copies of the low-power backscattered signal and combine them to improve the received signal-to-noise ratio (SNR). For the device-to-device (D2D) systems considered in [10], UEs can use backscattering to communicate with their peers and relay information for other D2D pairs. To maximize the aggregate throughput in the aforementioned scenario, an algorithm is proposed in [10] to optimize the beamforming of the power beacon signal and the selection of the reflection coefficients for relaying. A similar scenario is considered in [11], where D2D pairs use active transmission for forwarding information and backscattering for relaying the information of other pairs. A time division multiple access (TDMA) scheme is proposed to allocate different periods for energy harvesting, active transmission, and backscattering-based relaying for the D2D pairs to maximize the aggregate throughput. In [12], the throughput of a backscattering device is improved with the help of a relay that can use either active transmission or backscattering, depending on whether it has an embedded power source or not. In [13], a relaying scheme is proposed for a system consisting of a backscattering device and a harvest-then-transmit device by optimizing the time and power allocation to maximize the weighted sum rate. In [14], [15], the author considers a time-slotted backscatter communication system. A relay harvests energy in the first time slot, during which the transmitter reflects the incident power beacon. In the second time slot, the relay forwards the reflected data to the intended receiver.

Apart from the above, there is another use case of relaying in backscatter systems. Backscatter transmitters can reflect the incident signals to nearby relays that are equipped with stable power sources. Those relays can detect the backscattered signals and actively transmit them to the receivers. In [16], the authors consider a system where an unmanned aerial vehicle (UAV) acts as either a power source for the backscatter IoT device or as a relay between the IoT device and its intended receiver. In [17], the authors consider a downlink system with a multi-antenna transmitter and a single-antenna receiver, where a group of amplify-and-forward energy-harvesting relays is used for relaying data between the transmitter and receiver. The relays switch between active and passive relaying modes (i.e., active transmission and backscattering) to maximize the SNR of the system subject to energy harvesting constraints. In [18], the authors consider a system where each IoT device is associated with a dedicated relay (i.e., gateway) that has energy harvesting capability. The relay receives the backscattered data from the IoT device and relays the data to the BS using active transmission after harvesting sufficient energy. The authors formulate a sum-rate maximization problem, where the time duration allocated for energy harvesting, backscattering, and active transmission is optimized. In [19], beamforming of the power beacon is optimized to further improve the system aggregate throughput. In [1], a bipartite matching-based algorithm is proposed to pair backscattering IoT devices with a nearby UE relay in order to maximize the system connection density (i.e., maximize the number of IoT devices that meet a minimum SNR constraint).

Some other related works (e.g., [20]–[26]) addressed the case that IoT devices can perform both active transmission and backscattering. In a cognitive radio system considered in [20], secondary devices can use backscatter communication instead of harvest-then-transmit technique to reduce the interference on the primary user. In [21], deep reinforcement learning (DRL) is applied to obtain a policy that maximizes the aggregate data rate of the IoT devices that can use both of the aforementioned communication modes. In [22], [23], the IoT devices offload data for computation to a mobile edge computing server using either RF transmission or backscatter communications. A policy is obtained using DRL to determine which communication mode to be chosen based on the device state information (i.e., channel conditions, battery level, computation workload). On the other hand, optimizing the backscatter communication systems with a large number of backscattering-enabled IoT devices is challenging since it requires the knowledge of the channel state information (CSI) among the many devices coexisting in the same network, which necessitates extensive training and pilot signal transmissions for channel estimation. In [24], the authors consider an ambient backscatter communication system where an IoT device overlays in the time slot allocated for UE by backscattering data while using the downlink UE signal as an excitation signal. In this scheme, it is assumed that the channel conditions among the UEs and the IoT devices are unknown to the BS for UE-IoT device pairing. Hence, centralized and distributed association algorithms are developed using DRL. In [25], an algorithm is proposed for switching among harvest-then-transmit, bistatic backscattering, and ambient backscattering modes for data transmission. In [26], the authors consider a system where some IoT devices act as relays for other IoT devices. In the aforementioned system, ambient backscattering is used for transmitting data from an IoT device to its associated relay. On the other hand, bistatic backscattering is used for forwarding data from the relay to the destination.

When IoT devices are equipped with the necessary circuitry to transmit data using backscattering or RF transmission, they have more opportunities to use backscattering for data transmission. As an energy-efficient communication technology, backscattering can help IoT devices to save energy, increase battery lifetime, and reduce the rate of battery replacement [27]. However, using backscattering over longer communication range requires the presence of nearby backscatter receivers. Hence, UEs can be employed as backscatter receivers that receive the backscattered data from the IoT devices and relay them to the BS. On the other hand, active transmission can be used when there are no nearby UEs.

In this paper, we propose a communication mode selection scheme for narrowband IoT networks, where IoT devices can transmit their data using one of the two available communication modes. Those two modes are (a) active transmission and (b) backscattering data to a nearby UE which then forwards the data to the BS. In our work, we focus on those IoT applications with relaxed or loose latency requirements. Consequently, the proposed communication mode selection scheme has an IoT-oriented objective, which is to maximize the connection density, i.e., maximizing the number of IoT devices that satisfy a minimum SNR constraint. Our proposed scheme takes advantage of the presence of abundant UEs around the network and utilizes them as relays to forward the backscattered data from the IoT devices to the BS [1]. In this work, we use bistatic backscattering, where the BS acts as a power beacon source and the UEs act as backscattering receivers. When both active transmission and backscattering are enabled at the IoT devices, our proposed scheme helps IoT devices to select one of the communication modes according to the network topology. For example, if UE relays are available in the vicinity, then IoT devices have the opportunity to backscatter data as a means for energy-efficient communication. Using UEs as relays in the backscattering mode has several additional advantages. First, it reduces the expenditure of deploying dedicated readers (relays) or utilizing dedicated mobile readers (e.g., UAVs). Second, the IoT devices can have more opportunities to use backscattering to transmit data over a longer communication range with the help of UE relays, which can enhance the battery lifetime of IoT devices. Furthermore, UEs can be provided with economic rewards for relaying data of the IoT devices. On the other hand, with the absence of suitable UE relays in the vicinity, the IoT devices can utilize the active transmission mode. In this mode, two IoT devices can share a single subcarrier using uplink power-domain non-orthogonal multiple access (NOMA). Hence, it is necessary to determine the transmit power of a pair of IoT devices that share the same subcarrier in order to guarantee successful data decoding of the received signals at the BS using successive interference cancellation.

To this end, we formulate a communication mode selection problem as an optimization problem with the objective of maximizing the connection density. Each IoT device is assigned one of the communication modes (i.e., active transmission or backscattering). The communication mode selection needs to take into account several factors, including the network topology, CSI, and transmit power budgets. The contributions of this paper can be summarized as follows:

- We propose a communication mode selection scheme, where IoT devices can utilize active transmission or backscattering for communication. In the active transmission mode, two IoT devices share a single subcarrier using power-domain NOMA. In the backscattering mode, IoT devices can backscatter data to UE relays for data transmission.
- We formulate a connection density maximization problem to assign a communication mode for each IoT device. The formulated problem is a binary integer programming (BIP) problem, which can be solved optimally.
- Since the optimal algorithm has high computational complexity, we also solve the formulated problem by decomposing it into two subproblems, which can be solved by low-complexity suboptimal algorithms. For those IoT devices that are selected to use active transmission, we propose an algorithm based on bipartite matching to determine the IoT device pairing and the transmit power in an uplink power-domain NOMA system. For those IoT devices that are selected to use backscattering, a heuristic algorithm is used to associate them with UE relays and determines which IoT devices are scheduled to backscatter their data to the associated UE relays in the given time slot.
- Simulation results show that our proposed scheme can enhance the connection density of narrowband IoT systems by up to 64% when compared with using a single communication mode with perfect CSI in a 100 m^2 coverage area. Results also show that the suboptimal algorithm achieves a close performance to that of the optimal algorithm in most of the simulation scenarios.

The remainder of the paper is organized as follows. The system model is described in Section II. In Section III, we formulate the connection density maximization problem as a BIP problem, which can be optimally solved. We also propose suboptimal low-complexity algorithms to solve the formulated connection density maximization problem. We conduct performance evaluation of the proposed algorithms in Section IV. Section V concludes the paper.

Notations: In this paper, we use $\mathbb{C}$ to denote the set of complex numbers and $\mathbb{R}_+^N$ to denote the set of non-negative numbers. We denote the circularly symmetric complex Gaussian distribution with mean μ and variance σ^2 by $\mathcal{CN}(\mu, \sigma^2)$, and $\sim$ stands for "distributed as". We use $|h|$ to denote the absolute value of a complex number h. We also use $|\mathcal{D}|$ to denote the cardinality of a set $\mathcal{D}$.

II. System Model

Consider a single BS that provides coverage for a set of active IoT devices $\mathcal{D}$ and a set of available UE relays $\mathcal{U}$. The BS, the UEs and all the IoT devices are equipped with single antenna. Each IoT device is equipped with a battery and can transmit data either by (a) active transmission directly to the BS or (b) backscattering an incident power beacon signal from a single-antenna power source that is co-located at the BS to the associated UE, which in turn relays the backscattered data to the BS by active transmission as shown in Fig. 1.

We consider a time-slotted system. The communication mode selection is determined at the beginning of each time slot for the active IoT devices. Active transmission can be used to support communication without the need of relaying via a UE. This communication mode is useful in case of the absence of potential UE relays or the presence of UE relays with poor channel conditions for the backscattering link. On the other hand, with the presence of nearby UE relays, backscattering can be more energy-efficient for the IoT devices. In the backscattering mode, the BS acts as a carrier emitter and UE relays act as backscatter readers, i.e., bistatic backscattering is employed. Assigning the tasks of the carrier emitter and the backscatter reader to different devices (i.e., BS and UE relays, respectively) can increase the communication range of the backscattering systems.[1]

Dedicated subcarriers (i.e., frequency bands) are allocated for each communication mode, i.e., the IoT devices that use backscattering do not cause interference for the IoT devices that use active transmission and vice versa [26]. A set of narrowband subcarriers $\mathcal{S}$ is used for the active transmission mode. The IoT devices that transmit data using active transmission can share the same subcarrier using uplink power-domain NOMA [4]. Each subcarrier $s \in \mathcal{S}$ can be shared by at most two IoT devices [28], [29]. In most practical systems, no more than two IoT devices can share a single subcarrier because hardware complexity and processing delay increase with the devices on each subcarrier [29]. On the other hand, a

[1] In monostatic backscattering systems, where the carrier emitter and backscatter reader are the same device (e.g., BS), the communication range is limited to a few meters [6]. This makes direct communication between the BS and IoT devices via monostatic backscattering impractical.

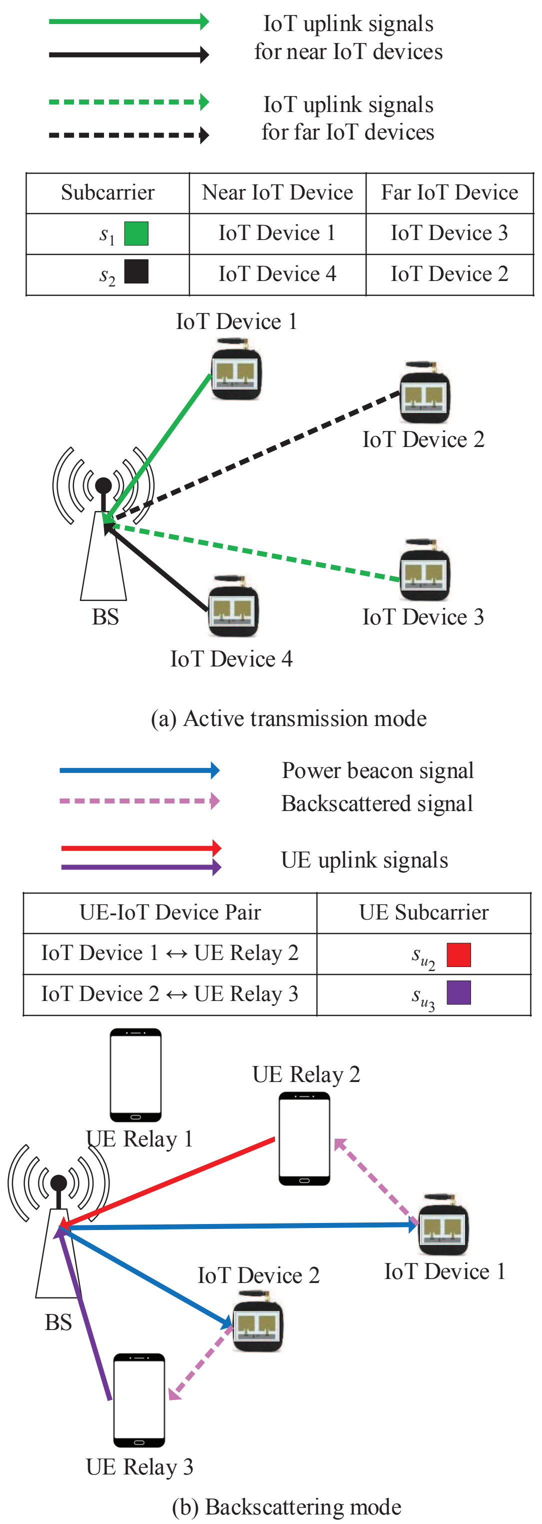

Fig. 1. System model. (a) Active transmission mode: The IoT device transmits data to the BS via active RF transmission. Each subcarrier can be accessed either by a single IoT device using orthogonal multiple access (OMA) or by a pair of IoT devices using NOMA. (b) Backscattering mode: An IoT device is associated with one of the available UE relays. The BS transmits a power beacon signal that is backscattered by the IoT device. The UE relay receives the backscattered signal and forwards it to the BS.

single subcarrier s_o is allocated for backscattering IoT devices. Hence, multiple UE-IoT device pairs can be scheduled within the same time slot over this subcarrier as long as they cause minimal interference to each other (i.e., each UE-IoT device pairs meets a minimum SNR requirement). Furthermore, each UE relay $u \in \mathcal{U}$ is allocated a dedicated subcarrier s_u that does not belong to the set of subcarriers assigned for serving the IoT devices (i.e., $s_u \notin S \cup \{s_o\}$).

The UE relay can forward the decoded data of the associated IoT device to the BS by appending them to the UE data, combining them with the UE data (by superposition similar to NOMA), or transmitting a dedicated IoT data packet. We consider that each UE $u \in \mathcal{U}$ is available to serve as a relay during the current time slot for a predetermined economic reward by the network.

Time is divided into slots with equal duration. A time slot is sufficient for a data packet transmission from an IoT device to the BS (i.e., active transmission), or from an IoT device to the BS via a UE relay (i.e., backscattering and relaying). During any given time slot, each IoT device d in the set of active IoT devices $\mathcal{D}$ has a data packet to transmit using one of the two communications modes. A subset of those devices can transmit their data packets in this time slot according to the decisions made by the communication mode selection scheme. If the data packet reception is successful, then the IoT device will receive an acknowledgment (ACK) packet from the BS. If the IoT device does not have additional packets in its buffer, it will then enter the sleep mode until a new data packet arrives. This is consistent with those scenarios where an IoT device needs to periodically obtain new measurements from the environment. When IoT device d receives an ACK packet and does not have new data packets to send, it is no longer a member of the set of active IoT devices $\mathcal{D}$ in the next time slot, i.e. $\mathcal{D} \longrightarrow \mathcal{D} \setminus \{d\}$.

The BS has information on the set of active IoT devices and the set of available UE relays in the coverage area after those devices have established connection via the random access procedure [30]. In addition, the BS acquires knowledge of the locations of the IoT devices and the UEs. We use $h^{(\text{mode})}_{m,n,s}(t) \in \mathbb{C}$ to denote the channel gain between device m and device n over subcarrier s at time slot t for a certain communication mode, where $m,\ n \in \{\text{BS}_i \mid 1 \le i \le I\} \cup \mathcal{U} \cup \mathcal{D}$ and $m \neq n$. Also, mode $\in \{\text{tr}, \text{bcs}\}$, where tr and bcs are abbreviations to denote the active transmission and backscattering modes, respectively. Moreover, we consider $h^{(\text{mode})}_{m,n,s}(t) = \sqrt{\ell_{m,n}}\hat{h}^{(\text{mode})}_{m,n,s}(t)$, where $\hat{h}^{(\text{mode})}_{m,n,s}(t) \in \mathbb{C}$ denotes the small-scale channel coefficient (e.g., Rayleigh fading) at time slot t such that $\hat{h}^{(\text{mode})}_{m,n,s}(t) \sim \mathcal{CN}(0,1)$. $\ell_{m,n} \in \mathbb{R}_+$ denotes the large-scale channel coefficient (e.g., path loss) between device m and device n. Since we assume channel reciprocity, we have $|h^{(\text{mode})}_{m,n,s}(t)| = |h^{(\text{mode})}_{n,m,s}(t)|$, $|\hat{h}^{(\text{mode})}_{m,n,s}(t)| = |\hat{h}^{(\text{mode})}_{n,m,s}(t)|$, and $\ell_{m,n} = \ell_{n,m}$. For simplifying the subsequent expressions, the time index t is dropped in the remaining part of this paper.

The channel gain between the BS and any of the IoT devices or the UE relays (i.e., $h^{(\text{tr})}_{\text{BS},d,s}$, $h^{(\text{bcs})}_{\text{BS},d,s_o}$, $d \in \mathcal{D}$ or h_{BS,u,s_u}, $u \in \mathcal{U}$) can be estimated at the BS side by receiving a pilot signal from the IoT devices and UE relays. Similarly, h_{d,u,s_o} can be estimated in a similar way, where IoT device d transmits a pilot signal that is receievd by UE relay u. In addition, $h^{(\text{bcs})}_{d,u,s_o}$ can also be estimated by the UE after receiving the reflection of the IoT device for a pilot signal from the BS. Given the received reflected signal at the UE, the pilot signal, and $h^{(\text{bcs})}_{\text{BS},d,s_o}$, the UE can estimate $h^{(\text{bcs})}_{d,u,s_o}$. In both methods, the UE reports the aforemtioned estimation to the BS [12].[2]

A. Active Transmission Mode

If IoT device d is scheduled to transmit in a given time slot and active transmission mode is used, then it will transmit a data packet to the BS with transmit power P_d over a subcarrier $s \in \mathcal{S}$. Once the BS has successfully decoded the received data, it transmits an ACK packet to the IoT device. Subsequently, the IoT device enters the sleep mode to save energy and does not attempt packet transmission over the subsequent time slots until a new data packet arrives from upper layer. On the other hand, if the BS fails to decode the received data packet, no ACK packet will be transmitted by the BS. In the latter case, the IoT device remains active and is considered for scheduling in one of the following time slots (according to the backoff mechanism followed by the IoT device) using either active transmission or backscattering.

The total system bandwidth allocated for active transmission mode is divided into a set of equal bandwidth subcarriers $\mathcal{S}$. Each subcarrier can be shared by up to two IoT devices using uplink power-domain NOMA [4]. For maximizing the connection density (scheduling the maximum number of IoT devices in the given subcarriers subject to the minimum SNR requirements), the transmit power of the IoT devices should be controlled. In addition, the transmit power should be minimized in order to reduce the energy consumption. In this paper, we assume a narrowband IoT system, i.e., the system bandwidth is less than the coherence bandwidth. Hence, $|h^{(\text{tr})}_{m,n,s}| = |h^{(\text{tr})}_{m,n,s'}|$ for all $s, s' \in \mathcal{S}$. Hence, subcarrier allocation in narrowband systems denotes pairing two IoT devices that can share access to a subcarrier $s \in \mathcal{S}$ using power-domain NOMA. In the following parts of the paper, the subcarrier index s is removed in order to simplify the notation of channel coefficient variables.

We introduce a binary variable $x_{d,d'}$, which is equal to 1 if IoT devices d and d' from set $\mathcal{D}$ share the same subcarrier (any subcarrier in $\mathcal{S}$) such that data from device d are decoded first.

$$x_{d,d'} \in \{0,1\}, \quad d \in \mathcal{D}, d' \in \mathcal{D} \cup \{d_o\} \setminus \{d\}, \tag{1}$$

where d_o is a dummy device index to indicate that an IoT device is allocated a given subcarrier without sharing it with other IoT devices using orthogonal multiple access (OMA). For example, if $x_{d,d_o} = 1$, then a single subcarrier is allocated to IoT device d using OMA. Consequently, the total number of NOMA pairs (including the OMA pairs of IoT devices with the dummy device d_o) cannot exceed the number of available subcarriers for active transmission,

$$\sum_{d \in \mathcal{D}} \sum_{d' \in \mathcal{D} \cup \{d_o\} \setminus \{d\}} x_{d,d'} \leq |\mathcal{S}|. \tag{2}$$

[2]The acquisition of CSI for all the links in each time slot may incur significant control overhead. The first approach to tackle this challenge is to update CSI every few time slots to reduce the control overhead. The second approach is to use geographical location information instead of CSI [31], e.g., we can assume that $|h_{d,u}| = c\sqrt{\ell_{d,u}}$, where c is a constant.

We determine the transmit power for each pair consisting of two distinct IoT devices from the set $\mathcal{D}$ assuming that those two IoT devices are allocated a shared subcarrier. In the formulation of the power allocation problem, a subcarrier is allocated to two IoT devices d_1 and d_2. Data from IoT device d_1 is decoded first. Hence, we introduce the binary variable a_d, which is equal to 1 if the BS can successfully decode the data from IoT device $d \in \{d_1, d_2\}$, i.e.,

$$a_d \in \{0,1\}, \quad d \in \{d_1, d_2\}. \tag{3}$$

When a_d is equal to 0, data from IoT device d cannot be decoded by the BS, i.e., the given pair of IoT devices cannot share any subcarrier using NOMA.

The IoT devices d_1 and d_2 use transmit powers P_{d_1} and P_{d_2} with maximum limits $P^{\max}_{d_1}$ and $P^{\max}_{d_2}$, respectively, i.e.,

$$0 \leq P_d \leq a_d P^{\max}_d, \quad d \in \{d_1, d_2\}. \tag{4}$$

Note that if a_d is equal to 0, then the transmit power P_d is equal to 0.

For successful decoding of the superimposed signals from the IoT devices d_1 and d_2 at the BS, it is required that the received signal-to-interference-plus-noise ratio (SINR) of d_1 and the received SNR of d_2 should be greater than a certain threshold $\gamma^{(\text{th})}_{\text{BS}}$. That is,

$$\frac{P_{d_1} |h^{(\text{tr})}_{\text{BS},d_1}|^2}{P_{d_2} |h^{(\text{tr})}_{\text{BS},d_2}|^2 + \sigma^2_{\text{BS}}} \geq a_{d_1} \gamma^{(\text{th})}_{\text{BS}}, \tag{5}$$

$$\frac{P_{d_2} |h^{(\text{tr})}_{\text{BS},d_2}|^2}{\sigma^2_{\text{BS}}} \geq a_{d_2} \gamma^{(\text{th})}_{\text{BS}}. \tag{6}$$

To successfully serve the NOMA pair consisting of the IoT devices d_1 and d_2 while consuming minimum power for data transmission, we formulate the power control problem as follows:

$$\begin{aligned} \underset{\substack{a_d, P_d \\ d \in \{d_1, d_2\}}}{\text{maximize}} \quad & a_{d_1} + a_{d_2} - w(P_{d_1} + P_{d_2}) \\ \text{subject to} \quad & \text{constraints } (3) - (6), \end{aligned} \tag{7}$$

where w is a positive weight factor that is selected such that pairing the two IoT devices and successfully decoding their data has higher priority than minimizing the total power consumption. This can be achieved by setting weight factor w to any value in the range $\left(0, \frac{1}{P^{\max}_{d_1} + P^{\max}_{d_2}}\right)$ (we set w to the maximum value in the aforementioned range). Problem (7) can be solved for each binary combination in $\mathcal{A} = \{(a_{d_1}, a_{d_2}) \mid a_{d_1} \in \{0,1\}, a_{d_2} \in \{0,1\}\}$ and we select the solution that maximizes the objective. In case of infeasibility, the objective is equal to $-\infty$. The optimal solutions can be obtained from Table I.

Note that when the objective value is equal to 0, both IoT devices d_1 and d_2 cannot meet the minimum SNR threshold requirements even with OMA (i.e., choosing one of the two devices to solely use the subcarrier) and hence cannot be served with active transmission mode in the current time slot. When the objective value is equal to $1 - wP^\star_{d_1}$ or $1 - wP^\star_{d_2}$, IoT devices d_1 and d_2 cannot share the given subcarrier using power-domain NOMA, but one of them can use it for active

TABLE I
OPTIMAL SOLUTION FOR PROBLEM (7)

$a^\star_{d_1}$	$a^\star_{d_2}$	$P^\star_{d_1}$	$P^\star_{d_2}$	Objective Value
0	0	0	0	0
0	1	0	$\frac{\gamma_{\text{BS}}^{(\text{th})}\sigma_{\text{BS}}^2}{\lvert h_{\text{BS},d_2}^{(\text{tr})}\rvert^2}$	$\begin{cases} 1-wP^\star_{d_2}, & \frac{\gamma_{\text{BS}}^{(\text{th})}\sigma_{\text{BS}}^2}{\lvert h_{\text{BS},d_2}^{(\text{tr})}\rvert^2} \leq P_{d_2}^{\max} \\ -\infty, & \text{otherwise} \end{cases}$
1	0	$\frac{\gamma_{\text{BS}}^{(\text{th})}\sigma_{\text{BS}}^2}{\lvert h_{\text{BS},d_1}^{(\text{tr})}\rvert^2}$	0	$\begin{cases} 1-wP^\star_{d_1}, & \frac{\gamma_{\text{BS}}^{(\text{th})}\sigma_{\text{BS}}^2}{\lvert h_{\text{BS},d_1}^{(\text{tr})}\rvert^2} \leq P_{d_1}^{\max} \\ -\infty, & \text{otherwise} \end{cases}$
1	1	$\frac{\gamma_{\text{BS}}^{(\text{th})}\sigma_{\text{BS}}^2(1+\gamma_{\text{BS}}^{(\text{th})})}{\lvert h_{\text{BS},d_1}^{(\text{tr})}\rvert^2}$	$\frac{\gamma_{\text{BS}}^{(\text{th})}\sigma_{\text{BS}}^2}{\lvert h_{\text{BS},d_2}^{(\text{tr})}\rvert^2}$	$\begin{cases} 2-w(P^\star_{d_1}+P^\star_{d_2}), & \frac{\gamma_{\text{BS}}^{(\text{th})}\sigma_{\text{BS}}^2(1+\gamma_{\text{BS}}^{(\text{th})})}{\lvert h_{\text{BS},d_1}^{(\text{tr})}\rvert^2} \leq P_{d_1}^{\max} \text{ and} \\ & \frac{\gamma_{\text{BS}}^{(\text{th})}\sigma_{\text{BS}}^2}{\lvert h_{\text{BS},d_2}^{(\text{tr})}\rvert^2} \leq P_{d_2}^{\max} \\ -\infty, & \text{otherwise} \end{cases}$

transmission with OMA. Finally, when the objective value is equal to $2 - w(P^\star_{d_1} + P^\star_{d_2})$, IoT devices d_1 and d_2 can share the allocated subcarrier using power-domain NOMA with the specified decoding order.

If there is no feasible solution when both a_{d_1} and a_{d_2} are equal to 1, then IoT devices d_1 and d_2 cannot share any subcarrier in the given decoding order. Hence, we introduce a binary variable b_{d_1,d_2} that is equal to 1 if and only if the optimal solution is obtained when a_{d_1} and a_{d_2} are equal to 1, i.e.,

$$b_{d_1,d_2} = a_{d_1} a_{d_2}. \tag{8}$$

When IoT devices d_1 and d_2 are paired, where data from IoT device d_1 are decoded first, then the transmit power of IoT device d_1 is denoted as $P_{d_1,d_2,1}$ and the transmit power of IoT device d_2 is denoted as $P_{d_1,d_2,2}$. $P_{d_1,d_2,1}$ and $P_{d_1,d_2,2}$ are set to take the values of $P^\star_{d_1}$ and $P^\star_{d_2}$, respectively.

In case of OMA, we set $d_2 = d_o$, where d_o is a dummy IoT device and $P_{d_2} = 0$. Hence, P_{d_1} can be evaluated as follows:

$$P_{d_1} = \begin{cases} \frac{\gamma_{\text{BS}}^{(\text{th})}\sigma_{\text{BS}}^2}{|h_{\text{BS},d_1}^{(\text{tr})}|^2}, & \frac{\gamma_{\text{BS}}^{(\text{th})}\sigma_{\text{BS}}^2}{|h_{\text{BS},d_1}^{(\text{tr})}|^2} \leq P_{d_1}^{\max}, \\ 0, & \frac{\gamma_{\text{BS}}^{(\text{th})}\sigma_{\text{BS}}^2}{|h_{\text{BS},d_1}^{(\text{tr})}|^2} > P_{d_1}^{\max}. \end{cases} \tag{9}$$

If the data of IoT device d_1 can be decoded in case of OMA, we set b_{d_1,d_o} to be equal to 1. The transmit power of IoT device d_1 is denoted as $P_{d_1,d_o,1}$ and the transmit power of dummy device d_o is denoted as $P_{d_1,d_o,2}$. $P_{d_1,d_o,1}$ and $P_{d_1,d_o,2}$ are set to take the values of P_{d_1} and 0, respectively.

The objective function aims to allocate the minimum transmit power to a pair of IoT devices while satisfying the minimum SNR threshold constraints. In narrowband systems, we need to evaluate the objective value for $|\mathcal{D}|^2$ potential pairs. The transmit power of any IoT device d that uses active transmission can be obtained for a given paired IoT device d' and the decoding order $r \in \{1, 2\}$. Note that satisfying the minimum SNR threshold for decoding the data at the BS is already taken into account while evaluating $P_{d,d',1}$ and $P_{d,d',2}$ for all $d \in \mathcal{D}$ and $d' \in \mathcal{D} \cup \{d_o\} \setminus \{d\}$.

The previous framework is applicable when more than two IoT devices access a subcarrier with NOMA. For grouping L IoT devices per subcarrier, we need to solve the power control problem for $\sum_{l=1}^{L} \prod_{j=0}^{l-1} |\mathcal{D}| - j$ NOMA groups, which is in the order of $|\mathcal{D}|^L$. The solution is obtained by evaluating the transmit power of the last decdoed IoT device in the group then evaluating the transmit powers of the remaining IoT devices in a descending decoding order. Hence, we obtain a binary indicator for whether the NOMA group can access a shared subcarrier (similar to b_{d_1,d_2} when $L = 2$) and the required tranmsit power values (similar to $P_{d_1,d_2,1}$, $P_{d_1,d_2,2}$ when $L = 2$). For example, when $L = 3$ and the data of IoT devices d_1, d_2, and d_3 are decoded in the aforemnetioned order, we obtain b_{d_1,d_2,d_3}, $P_{d_1,d_2,d_3,1}$, $P_{d_1,d_2,d_3,2}$, and $P_{d_1,d_2,d_3,3}$. In practical systems, increasing the number of devices per subcarrier in power-domain NOMA systems results in a higher hardware complexity and processing delays [28], [29].

Each IoT device can be paired with only one IoT device, i.e.,

$$\sum_{d' \in \mathcal{D} \cup \{d_o\} \setminus \{d\}} x_{d,d'} + \sum_{d'' \in \mathcal{D} \setminus \{d\}} x_{d'',d} \leq 1, \quad d \in \mathcal{D}. \tag{10}$$

At the BS, we consider that the received packets of IoT devices d and d' pair can be successfully decoded if their received SNRs, denoted by $\gamma_{d,d',\text{BS},1}$ and $\gamma_{d,d',\text{BS},2}$, respectively, are greater than a certain threshold $\gamma_{\text{BS}}^{(\text{th})}$. The expression for $\gamma_{d,d',\text{BS},1}$ is given by

$$\gamma_{d,d',\text{BS},1} = \frac{P_{d,d',1}|h_{\text{BS},d}^{(\text{tr})}|^2}{P_{d,d',2}|h_{\text{BS},d'}^{(\text{tr})}|^2 + \sigma_{\text{BS}}^2}, \; d \in \mathcal{D}, d' \in \mathcal{D} \cup \{d_o\} \setminus \{d\}, \tag{11}$$

where σ_{BS}^2 is the noise power at the BS. The expression of $\gamma_{d,d',\text{BS},2}$ is given by

$$\gamma_{d,d',\text{BS},2} = \frac{P_{d,d',2}|h_{\text{BS},d'}^{(\text{tr})}|^2}{\sigma_{\text{BS}}^2}, \quad d \in \mathcal{D}, d' \in \mathcal{D} \cup \{d_o\} \setminus \{d\}. \tag{12}$$

Then, the minimum SNR threshold constraint can be expressed as

$$\gamma_{d,d',r} \geq x_{d,d'} \gamma_{\text{BS}}^{(\text{th})}, \quad d \in \mathcal{D}, d' \in \mathcal{D} \cup \{d_o\} \setminus \{d\}, r \in \{1, 2\}. \tag{13}$$

The solution of the power control problem (7) (i.e., $b_{d,d'}$, $P_{d,d',1}$ and $P_{d,d',2}$) for each pair of IoT devices ensures satisfying constraint (13). This is because after the power control problem has been solved, we obtain a binary variable $b_{d,d'}$, which is equal to 1 if and only if the IoT devices pair d and d' can share a subcarrier using NOMA (i.e., the power control problem returns a feasible solution that satisfies the maximum power constraint and minimum SNR threshold). The minimum SNR threshold constraint can be rewritten as

$$x_{d,d'} \leq b_{d,d'}, \quad d \in \mathcal{D}, d' \in \mathcal{D} \cup \{d_o\} \setminus \{d\}. \tag{14}$$

This constraint enforces that if a pair of IoT devices cannot share a subcarrier using NOMA, then they will not be paired together.

B. Backscattering Mode

If IoT device d is scheduled to transmit in a given time slot and backscattering mode is used, then it will transmit a data packet by modulating an incident power beacon signal from the BS which has a transmit power of P_{BS}. The backscattered signal is received by an associated UE relay u over a common backscattering subcarrier s_o. Subsequently, the UE relay forwards the data to the BS using a constant transmit power of P_u. When BS has successfully decoded the received data, it transmits an ACK packet to the IoT device. Similar to the active transmission case, the IoT device enters the sleep mode to save energy until a new data packet arrives. On the other hand, if the IoT device does not receive an ACK from the BS, the IoT device may attempt packet retransmission in the following time slot. We assume that the UE relay drops the buffered data by the end of each time slot.

The BS needs to successfully decode the forwarded packet by any UE relay u over its allocated subcarrier s_u. This requires that the received SNR $\gamma_{u,\text{BS}}$ is greater than a certain threshold $\gamma_{\text{BS}}^{(\text{th})}$. The expression of $\gamma_{u,\text{BS}}$ is given by:

$$\gamma_{u,\text{BS}} = \frac{P_u |h_{\text{BS},u}|^2}{\sigma_{\text{BS}}^2}, \quad u \in \mathcal{U}. \tag{15}$$

Without loss of generality, we assume that the set of UE relays $\mathcal{U}$ only includes UEs which have good channel conditions for forwarding data to the BS (i.e., $\frac{P_u |h_{\text{BS},u}|^2}{\sigma_{\text{BS}}^2} \geq \gamma_{\text{BS}}^{(\text{th})}$).

We introduce a binary variable $z_{d,u}$, which is equal to 1 if IoT device d is associated with UE relay u and the UE-IoT device pair (d,u) is scheduled for data transmission during the current time slot. Otherwise, $z_{d,u}$ is equal to 0.

$$z_{d,u} \in \{0,1\}, \quad d \in \mathcal{D}, u \in \mathcal{U}. \tag{16}$$

Each IoT device d can be associated with a single UE relay u. Then, we have

$$\sum_{u \in \mathcal{U}} z_{d,u} \leq 1, \quad d \in \mathcal{D}. \tag{17}$$

In addition, each UE relay can receive backscattered data from a single IoT device, i.e.,

$$\sum_{d \in \mathcal{D}} z_{d,u} \leq 1, \quad u \in \mathcal{U}. \tag{18}$$

IoT device d transmits data by modulating an incident power beacon signal from the BS which has a transmit power of P_{BS}. The backscattered signal is received by an associated UE relay u. Let $\gamma_{d,u}$ denote the received SNR at UE relay device u when device d backscatters the data. The expression is given by

$$\gamma_{d,u} = \frac{z_{d,u} G_{d,u}}{\sum_{k \in \mathcal{D} \setminus \{d\}} \sum_{v \in \mathcal{U} \setminus \{u\}} z_{k,v} G_{k,u} + \sigma_u^2}, \quad d \in \mathcal{D}, u \in \mathcal{U}, \tag{19}$$

where $G_{d,u} = \zeta_d P_{\text{BS}} |h_{\text{BS},d}^{(\text{bcs})}|^2 |h_{d,u}^{(\text{bcs})}|^2$, ζ_d is the magnitude of the reflection coefficient of IoT device d while backscattering incident power beacon signal, and σ_u^2 is the noise power at UE u. At the UE, the backscattered signals from non-associated IoT devices are treated as noise during decoding. Also, the power beacon signal from the BS is assumed to be known at the UE and can be subtracted from the received signal using self-interference cancellation [10]. Upon successful data decoding at the UE relay, the received SNR at the UE $\gamma_{d,u}$ should be greater than a certain threshold $\gamma_u^{(\text{th})}$, i.e.,

$$\frac{z_{d,u} G_{d,u}}{\sum_{k \in \mathcal{D} \setminus \{d\}} \sum_{v \in \mathcal{U} \setminus \{u\}} z_{k,v} G_{k,u} + \sigma_u^2} \geq z_{d,u} \gamma_u^{(\text{th})}, \quad d \in \mathcal{D}, u \in \mathcal{U}. \tag{20}$$

Constraint (20) can be rewritten as

$$z_{d,u} \left(G_{d,u} - \sigma_u^2 \gamma_u^{(\text{th})} \right) \geq \sum_{k \in \mathcal{D} \setminus \{d\}} \sum_{v \in \mathcal{U} \setminus \{u\}} y_{d,u,k,v} G_{k,u} \gamma_u^{(\text{th})}, \quad d \in \mathcal{D}, u \in \mathcal{U}, \tag{21}$$

where $y_{d,u,k,v} = z_{d,u} z_{k,v}$ and it is a binary variable defined by the following constraints:

$$y_{d,u,k,v} \in \{0,1\}, \quad d \in \mathcal{D}, u \in \mathcal{U}, k \in \mathcal{D} \setminus \{d\}, v \in \mathcal{U} \setminus \{u\} \tag{22}$$

$$y_{d,u,k,v} \leq z_{d,u}, \quad d \in \mathcal{D}, u \in \mathcal{U}, k \in \mathcal{D} \setminus \{d\}, v \in \mathcal{U} \setminus \{u\} \tag{23}$$

$$y_{d,u,k,v} \leq z_{k,v}, \quad d \in \mathcal{D}, u \in \mathcal{U}, k \in \mathcal{D} \setminus \{d\}, v \in \mathcal{U} \setminus \{u\} \tag{24}$$

$$y_{d,u,k,v} \geq z_{d,u} + z_{k,v} - 1, \quad d \in \mathcal{D}, u \in \mathcal{U}, k \in \mathcal{D} \setminus \{d\}, v \in \mathcal{U} \setminus \{u\}. \tag{25}$$

III. Communication Mode Selection Problem Formulation and Proposed Algorithm

In this section, we formulate the communication mode selection problem which can be solved optimally. Then, we decompose it into two subproblems that can be solved using low-complexity proposed algorithms.

A. Communication Mode Selection Problem Formulation

Each IoT device can either use active transmission mode or backscattering mode, i.e.,

$$\sum_{d' \in \mathcal{D} \cup \{d_o\} \setminus \{d\}} x_{d,d'} + \sum_{d'' \in \mathcal{D} \setminus \{d\}} x_{d'',d} + \sum_{u \in \mathcal{U}} z_{d,u} \leq 1, \quad d \in \mathcal{D}. \tag{26}$$

The communication mode selection problem can be formulated as a connection density maximization problem as follows:

$$\underset{\mathbf{X},\,\mathbf{Z},\,\mathbf{Y}}{\text{maximize}} \sum_{d\in\mathcal{D}} \Bigg(\sum_{d'\in\mathcal{D}\cup\{d_o\}\setminus\{d\}} x_{d,d'} + \sum_{d''\in\mathcal{D}\setminus\{d\}} x_{d'',d} + \sum_{u\in\mathcal{U}} z_{d,u} \Bigg) \tag{27}$$

$$\text{subject to} \quad \text{constraints } (1)-(2), (14), (16)-(18), (21)-(26),$$

where $\mathbf{X} = [x_{d,d'}]$ represents the IoT device pairing matrix for the active transmission mode, $d \in \mathcal{D}, d' \in \mathcal{D}\cup\{d_o\}\setminus\{d\}$. $\mathbf{Z} = [z_{d,u}]$ is the UE-IoT device pairing matrix for the backscattering mode, where $d \in \mathcal{D}, u \in \mathcal{U}$. $\mathbf{Y} = [y_{d,u,k,v}]$ is the matrix of the auxiliary binary variables $y_{d,u,k,v}$ for all $d \in \mathcal{D}, u \in \mathcal{U}, k \in \mathcal{D}\setminus\{d\}, v \in \mathcal{U}\setminus\{u\}$. Note that the term $\sum_{d\in\mathcal{D}}\sum_{d'\in\mathcal{D}\cup\{d_o\}\setminus\{d\}} x_{d,d'}$ represents the total number of IoT devices that can successfully transmit their data with active transmission with OMA or NOMA as the first user for decoding at the BS. The term $\sum_{d\in\mathcal{D}}\sum_{d''\in\mathcal{D}\setminus\{d\}} x_{d'',d}$ represents the total number of IoT devices that can successfully transmit their data with active transmission with NOMA as the second user for decoding in the NOMA pair. Then, the term $\sum_{d\in\mathcal{D}}\sum_{u\in\mathcal{U}} z_{d,u}$ represents the total number of IoT devices that can successfully transmit their data packets by backscattering the data signals to their respective associated UE relays.

The formulated problem is a BIP problem that can be solved optimally using exact algorithms such as branch-and-bound and exhaustive search. However, these algorithms have exponential complexity. We need to solve for $|\mathcal{D}|^2$ binary variables in matrix $\mathbf{X}$, $|\mathcal{D}||\mathcal{U}|$ binary variables in matrix $\mathbf{Z}$, and $|\mathcal{D}|(|\mathcal{D}|-1)|\mathcal{U}|(|\mathcal{U}|-1)$ binary variables in matrix $\mathbf{Y}$. Hence, in the worst case (i.e., with exhaustive search), the computational complexity is given by $O(2^{|\mathcal{D}|^2|\mathcal{U}|^2})$. In the following subsections, we decompose the problem into two subproblems (one subproblem for each communication mode) and then solve each subproblem using a suboptimal algorithm with low computational complexity.

B. Active Transmission Subproblem

In the first subproblem, we consider a set of IoT devices $\mathcal{D}^{(\text{tr})} = \mathcal{D}$ for active transmission mode. Given a set of subcarriers, the objective is to form as many NOMA pairs as possible in order to maximize the overall connection density. First, after sorting the elements from the set of IoT devices $\mathcal{D}^{(\text{tr})}$ based on the channel gain from the BS, the set is further divided into two subsets $\mathcal{D}^{(\text{tr-n})}$ and $\mathcal{D}^{(\text{tr-f})}$ for near and far IoT devices, respectively. Then, we form NOMA pairs by pairing IoT devices from both subsets in order to solve the following active transmission subproblem:

$$\underset{\mathbf{X}}{\text{maximize}} \sum_{d\in\mathcal{D}^{(\text{tr-n})}} \sum_{d'\in\mathcal{D}^{(\text{tr-f})}} 2x_{d,d'} + \sum_{d\in\mathcal{D}^{(\text{tr})}} x_{d,d_o} \tag{28}$$

$$\begin{aligned} \text{subject to} \quad & x_{d,d'} \in \{0,1\}, \quad d \in \mathcal{D}^{(\text{tr-n})}, d' \in \mathcal{D}^{(\text{tr-f})}\cup\{d_o\} \\ & \sum_{d'\in\mathcal{D}^{(\text{tr-f})}\cup\{d_o\}} x_{d,d'} \le 1, \quad d \in \mathcal{D}^{(\text{tr-n})} \\ & \sum_{d''\in\mathcal{D}^{(\text{tr-n})}} x_{d'',d} \le 1, \quad d \in \mathcal{D}^{(\text{tr-f})} \\ & x_{d,d'} \le b_{d,d'}, \quad d \in \mathcal{D}^{(\text{tr-n})}, d' \in \mathcal{D}^{(\text{tr-f})}\cup\{d_o\} \\ & \sum_{d\in\mathcal{D}^{(\text{tr-n})}} \sum_{d'\in\mathcal{D}^{(\text{tr-f})}\cup\{d_o\}} x_{d,d'} \le |\mathcal{S}|, \end{aligned}$$

Algorithm 1: NOMA Pairing of IoT Devices Algorithm

1 **Input**: $\gamma_{\text{BS}}^{(\text{th})}$, $\mathcal{D}$, $|\mathcal{S}|$
2 $\mathcal{D}^{(\text{tr})} \longleftarrow \emptyset$
3 $x_{d,d'} := 0$ for all $d \in \mathcal{D}, d' \in \mathcal{D}\cup\{d_o\}\setminus\{d\}$
4 Sort the IoT devices of $\mathcal{D}$ in descending order according to the magnitude of the channel gain $|h_{\text{BS},d}^{(\text{tr})}|$
5 $\mathcal{D}^{(\text{tr-n})} \longleftarrow$ The nearest 50% of the IoT devices of $\mathcal{D}$
6 $\mathcal{D}^{(\text{tr-f})} \longleftarrow$ The farthest 50% of the IoT devices of $\mathcal{D}$
7 $w_{d_n,d_f} := 0$ for all $d_n \in \mathcal{D}^{(\text{tr-n})}$, $d_f \in \mathcal{D}^{(\text{tr-f})}$
8 **for** $d_n \in \mathcal{D}^{(\text{tr-n})}$ **do**
9   **for** $d_f \in \mathcal{D}^{(\text{tr-f})}$ **do**
10   Evaluate b_{d_n,d_f} from (8) after solving the power allocation problem using Table I
11         $w_{d_n,d_f} := b_{d_n,d_f}$
12   **end**
13 **end**
14 Solve problem (28) as a maximum cardinality bipartite one-to-one matching problem to obtain x_{d_n,d_f} for all $d_n \in \mathcal{D}^{(\text{tr-n})}$, $d_f \in \mathcal{D}^{(\text{tr-f})}$ (the maximum number of pairs is $|\mathcal{S}|$). Allocate a unique subcarrier for each matched pair of IoT devices.
15 `// Allocating the remaining subcarriers for IoT devices with OMA`
16 **if** Number of NOMA pairs $< |\mathcal{S}|$ **then**
17   Allocate each remaining subcarrier to a non-paired IoT device $d^{(\text{OMA})}$ from $\mathcal{D}$ that satisfies the condition $\left(\frac{\gamma_{\text{BS}}^{(\text{th})}\sigma_{\text{BS}}^2}{|h_{\text{BS},d^{(\text{OMA})}}|^2} \le P_{d^{(\text{OMA})}}^{\max}\right)$ until all subcarriers are allocated and set $x_{d^{(\text{OMA})},d_o} := 1$
18 **end**
19 $\mathcal{D}^{(\text{tr})} \longleftarrow \{d \mid x_{d,d'} = 1 \text{ OR } x_{d'',d} = 1, d' \in \mathcal{D}\cup\{d_o\}\setminus\{d\}, d'' \in \mathcal{D}\setminus\{d\}\}$
20 **Output**: matrix $\mathbf{X}$ and set $\mathcal{D}^{(\text{tr})}$

where the term $\sum_{d\in\mathcal{D}^{(\text{tr-n})}}\sum_{d'\in\mathcal{D}^{(\text{tr-f})}} 2x_{d,d'}$ represents the number of IoT devices that share subcarriers using NOMA, and the term $\sum_{d\in\mathcal{D}^{(\text{tr})}} x_{d,d_o}$ represents the number of IoT devices that access subcarriers with OMA. Note that when $x_{d,d'}$ is equal to 1, the IoT device NOMA pair (or OMA IoT device) can be allocated any of the available $|\mathcal{S}|$ subcarriers. To solve this problem, we propose Algorithm 1. The IoT devices are divided into two subsets for near and far IoT devices as shown in Steps 4 – 6. Bipartite matching [32] is used for pairing IoT devices from both sets to share subcarriers with NOMA as shown in Steps 7 – 14. In particular, the steps for constructing the matching graph are shown in Steps 8 – 13, where there are two disjoint sets of vertices representing the two sets of IoT devices. Edges are constructed between a pair of vertices consisting a near and a far IoT device based on the outcome of solving the NOMA power control problem (i.e., when the near and far IoT devices form an eligible NOMA pair if b_{d_n,d_f} is evaluated according to (8) to be equal to 1). If there are any remaining subcarriers that have not been allocated, they can be assigned to IoT devices for access using OMA as shown in Steps 15 – 18. We obtain the NOMA pairing matrix $\mathbf{X}$ and the set of IoT devices that are selected to use active transmission mode $\mathcal{D}^{(\text{tr})}$. Hence, this set of devices will not be considered when solving the backscattering subproblem.

To determine the computational complexity of Algorithm 1 that is used to solve the active transmission subproblem, let the cardinality of those two sets be equal to D (i.e., $|\mathcal{D}^{(\text{tr-f})}| = |\mathcal{D}^{(\text{tr-n})}| = D$). The computational complexity for sorting the IoT devices according to the channel gain is $O(D\log(D))$. In addition, the computational complexity for solving the power allocation problem for each pair of IoT devices is $O(D^2)$. Furthermore, the computational complexity for solving the bipartite matching problem with sets of size D and up to D^2 edges is $O(D^3)$. Finally, the computational complexity of allocating the remaining subcarriers using OMA is $O(|\mathcal{S}|)$ in the worst case. The overall computational complexity of Algorithm 1 is $O(D^2 + D^3 + |\mathcal{S}|) = O(D^3)$, assuming $|\mathcal{S}| < D$.

C. Backscattering Subproblem

In the second subproblem, we focus on the UE-IoT device pairing and scheduling in the backscattering mode. Hence, our objective is to have the maximum number of UE-IoT device pairs that can communicate concurrently in the same time slot while each pair meets the minimum SNR threshold expressed in (21). In this subproblem, we consider associating UE relays only with IoT devices that have not been assigned to use active transmission after solving the active transmission subproblem. We denote this set of IoT devices as $\mathcal{D}^{(\text{bcs})} = \mathcal{D}\backslash\mathcal{D}^{(\text{tr})}$.

First, we associate each UE u (one by one) with an IoT device d_u having the maximum channel gain (i.e., the nearest IoT device in most cases). Let q denote a UE-IoT device pair. Then, we form the set of UE-IoT device pairs $\mathcal{Q}$ by including all UE-IoT device pair elements $q = (d_u, u)$ for all $u \in \mathcal{U}$. The IoT device d_u associated with UE relay u is given by:

$$d_u = \arg\max_{d\in\mathcal{D}_u} G_{d,u}, \quad u \in \mathcal{U}, \mathcal{D}_u \neq \emptyset, \tag{29}$$

Algorithm 2: UE-IoT Device Pairing and Scheduling Algorithm

Input: $\gamma_u^{(\text{th})}$, $\mathcal{D}^{(\text{bcs})} \longleftarrow \mathcal{D} \setminus \mathcal{D}^{(\text{tr})}$, $G_{d,u}$ for all $d \in \mathcal{D}^{(\text{bcs})}, u \in \mathcal{U}$
$\mathcal{Q} \longleftarrow \emptyset$, $\mathcal{U}^{(\text{bcs})} \longleftarrow \emptyset$, $z_{d,u} := 0$ for all $d \in \mathcal{D}$, $u \in \mathcal{U}$, $\mathcal{D}_u \longleftarrow \mathcal{D}^{(\text{bcs})}$ for all $u \in \mathcal{U}$
for $u \in \mathcal{U}$ **do**
  if $\mathcal{D}_u\ != \emptyset$ **then**
    Determine the IoT device d_u associated with UE u according to (29) and the UE-IoT device pair element $q := (d_u, u)$.
    $\mathcal{Q} \longleftarrow \mathcal{Q} \cup \{q\}$, $\mathcal{U}^{(\text{bcs})} \longleftarrow \mathcal{U}^{(\text{bcs})} \cup \{u\}$
    if $u + 1 \leq |\mathcal{U}|$ **then**
      $\mathcal{D}_{u+1} \longleftarrow \mathcal{D}_u \setminus \{d\}$
    end
  else
    break
  end
end
$q := (d_u, u)$, where $(d_u, u) := \arg\max_u G_{d_u,u}$
if $G_{d_u,u}/\sigma_u^2 \geq \gamma_u^{(\text{th})}$ **then**
  // $\mathcal{Q}_a$ ($\mathcal{U}_a$) is the set of scheduled UE-IoT pairs (UEs). $\mathcal{Q}_b$ ($\mathcal{U}_b$) is the set of non-scheduled UE-IoT pairs (UEs)
  $z_{d_u,u} := 1$, $\mathcal{Q}_a \longleftarrow \{q\}$, $\mathcal{Q}_b \longleftarrow \mathcal{Q} \setminus \{q\}$, $\mathcal{U}_a \longleftarrow \{u\}$, $\mathcal{U}_b \longleftarrow \mathcal{U}^{(\text{bcs})} \setminus \{u\}$
  while $\mathcal{Q}_a! = \mathcal{Q}$ **do**
    $\gamma^{(\text{temp})} := -1$, $q^{(\text{temp})} :=$ NULL
    for $q_b \in \mathcal{Q}_b$ **do**
      // Evaluating SINR for the non-scheduled UE-IoT pair $q_b := (d_{u''}, u'')$ given the set of scheduled pairs $\mathcal{Q}_a$ (denoted as $\gamma_{q_b|\mathcal{Q}_a}$)
      $\gamma_{q_b|\mathcal{Q}_a} := \frac{G_{d_{u''},u''}}{\sum_{u\in\mathcal{U}_a} G_{d_u,u''}+\sigma^2_{u''}}$
      // $G_{d_u,u''}$ is the interference caused by scheduled IoT device d_u on non-scheduled UE relay u''
      if $\gamma_{q_b|\mathcal{Q}_a} \geq \gamma_u^{(\text{th})}$ **then**
        for $q_a \in \mathcal{Q}_a$ **do**
          // Evaluating SINR for scheduled UE-IoT pair $q_a := (d_u, u)$ assuming that non-scheduled pair $q_b : (d_{u''}, u'')$ will be scheduled (denoted as $\gamma_{q_a|q_b}$)
          $\gamma_{q_a|q_b} := \frac{G_{d_u,u}}{\sum_{u'\in\mathcal{U}_a\setminus\{u\}} G_{d_{u'},u}+G_{d_{u''},u}+\sigma_u^2}$
          // $G_{d_{u'},u}$ ($G_{d_{u''},u}$) is the interference caused by scheduled (non-scheduled) IoT device $d_{u'}$ ($d_{u''}$) on UE relay u
        end
        if $\gamma_{q_a|q_b} \geq \gamma_u^{(\text{th})}$ for all $q_a \in \mathcal{Q}_a$ && $\frac{1}{|\mathcal{Q}_a|}\sum_{q_a\in\mathcal{Q}_a}\gamma_{q_a|q_b} > \gamma^{(\text{temp})}$ **then**
          $\gamma^{(\text{temp})} := \frac{1}{|\mathcal{Q}_a|}\sum_{q_a\in\mathcal{Q}_a}\gamma_{q_a|q_b}$
          $q^{(\text{temp})} := q_b$, where $q_b := (d_{u''}, u'')$
        end
      end
    end
    if $q^{(\text{temp})}\ != $ NULL **then**
      $z_{d_{u''},u''} := 1$, $\mathcal{Q}_a \longleftarrow \mathcal{Q}_a \cup \{q^{(\text{temp})}\}$, $\mathcal{Q}_b \longleftarrow \mathcal{Q}_b \setminus \{q^{(\text{temp})}\}$, $\mathcal{U}_a \longleftarrow \mathcal{U}_a \cup \{u''\}$, $\mathcal{U}_b \longleftarrow \mathcal{U}_b \setminus \{u''\}$
    else
      break
    end
  end
end
Output: matrix $\mathbf{Z}$

where $\mathcal{D}_u$ is the set of IoT devices that can be paired with UE u. $\mathcal{D}_u$ includes all the IoT devices in $\mathcal{D}^{(\text{bcs})}$ except those that have been paired with other UE relays. Then, we have the set of UE-IoT device pairs $\mathcal{Q} = \{q = (d_u, u) \mid u \in \mathcal{U}, \mathcal{D}_u \neq \emptyset\}$. Note that each element q of the set $\mathcal{Q}$ is a pair of a UE relay u and its associated IoT device d_u, i.e., $q = (d_u, u)$. The backscattering subproblem can be formulated as follows:

$$\begin{aligned} &\underset{\mathbf{Z},\,\mathbf{Y}}{\text{maximize}} && \sum_{u\in\mathcal{U},\mathcal{D}_u\neq\emptyset} z_{d_u,u} \\ &\text{subject to} && \text{constraints } (16)-(18),(21)-(25). \end{aligned} \tag{30}$$

Although the aforementioned problem is a BIP problem, it has a lower number of binary variables to evaluate than problem (27). The reason is that the maximum number of UE-IoT device pairs $|\mathcal{Q}|$ is equal to $\min\{|\mathcal{D}||\mathcal{U}|\}$. Hence, we only need to solve for $|\mathcal{Q}|^2+|\mathcal{Q}|$ binary variables. Assuming exhaustive search, the computational complexity is given by $O(2^{|\mathcal{Q}|^2})$. To further reduce the computational complexity, we propose a heuristic algorithm with polynomial complexity to schedule the UE-IoT device pairs that can communicate concurrently in a single time slot. The proposed UE-IoT device pairing and scheduling algorithm to solve the backscattering subproblem is shown in Algorithm 2. In Steps 3 – 13, we describe the UE-IoT device pairing, which is based on associating each UE u to an IoT device with the maximum value of $G_{d,u}$. Steps 14 – 42 describe the heuristic algorithm for determining the UE-IoT device pairs that are scheduled in the current time slot. In particular, in Steps 14 – 17, the UE-IoT device pair $q=(d_u,u)$ with the maximum channel gain $G_{d_u,u}$ is chosen as the first scheduled pair if and only if the SNR is greater than the minimum threshold $\gamma_u^{(\text{th})}$. We introduce two intermediary sets $\mathcal{Q}_a$ and $\mathcal{Q}_b$ ($\mathcal{U}_a$ and $\mathcal{U}_b$) to represent the sets of scheduled and non-scheduled UE-IoT device pairs (UE relays), respectively. In Steps 21 – 23, we evaluate the SINR for one non-scheduled UE-IoT device pair $q_b\in\mathcal{Q}_b$ given the set of scheduled UE-IoT device pairs $\mathcal{Q}_a$. If the SINR is greater than the minimum threshold, then we evaluate the SINR for all the scheduled UE-IoT device pairs in set $\mathcal{Q}_a$ assuming that the pair q_b is scheduled as shown in Steps 24 – 29. We choose a non-scheduled UE-IoT device pair $q^{(\text{temp})}$ that satisfies the following conditions: (a) it meets the minimum SNR requirement given the previously scheduled UE-IoT device pairs, (b) the previously scheduled pairs can still meet the minimum SNR requirement if $q^{(\text{temp})}$ is scheduled, and (c) among all the non-scheduled UE-IoT device pairs satisfying the previous two conditions, the average SINR for all scheduled UE-IoT device pairs is maximum when the UE-IoT device pair $q^{(\text{temp})}$ is added to the scheduled UE-IoT device pairs as shown in Steps 30 – 33. The steps described in the while loop from Step 18 to Step 41 are repeated for multiple iterations until either all the UE-IoT device pairs are scheduled or none of the non-scheduled pairs can be scheduled without causing the scheduled pairs not to meet the minimum SNR requirement. After running this algorithm, we obtain the UE-IoT pairing matrix $\mathbf{Z}$. In summary, Algorithm 2 keeps adding UE-IoT device pairs one-by-one until no more pairs can be added without causing those already added pairs to fail to meet the minimum SNR requirements.

To evaluate the computational complexity of Algorithm 2 that is used to solve the backscattering subproblem, we notice that the maximum number of UE-IoT device pairs is bound by the number of available UE relays., i.e., $|\mathcal{U}|$. Hence, the computational complexity of UE-IoT device pairing is $O(|\mathcal{U}|)$.

Algorithm 3: Communication Mode Selection Algorithm

1 **for** $t>0$ **do**
2 // Updating/Obtaining Information about IoT Devices:
3 Update the set of IoT devices $\mathcal{D}$: Add the newly arriving IoT devices and remove the successfully served IoT devices in time slot $t-1$.
4 Obtain channel information $h_{\text{BS},d}$ of the newly arriving IoT devices.
5 **if** $t \bmod T_{\mathcal{D}}^{\text{update}} == 0$ **then**
6 Update channel information $h_{\text{BS},d}$ of the IoT devices which have not been served during previous time slot $t-1$.
7 **end**
8 // Updating/Obtaining Information about UE Relays:
9 Obtain channel information $h_{\text{BS},u}$ of the newly arriving UEs to determine their eligibility for relaying IoT data by checking whether $\frac{P_u|h_{\text{BS},u}|^2}{\sigma_{\text{BS}}^2}$ is greater than decoding threshold $\gamma_{u,\text{BS}}$.
10 Update the set of UE relays $\mathcal{U}$: Add the newly arriving UEs that are ready (and eligible) to act as relays and remove the UEs leaving the coverage area or unavailable for relaying IoT data.
11 **if** $t \bmod T_{\mathcal{U}}^{\text{update}} == 0$ **then**
12 Update channel information $h_{\text{BS},u}$ of the existing active UE relays from previous time slot $t-1$.
13 **end**
14 // Updating/Obtaining Information about UE-IoT Device Links:
15 Obtain channel information $h_{d,u}$ of the new UE-IoT device pairs.
16 **if** $t \bmod T_{\mathcal{D},\mathcal{U}}^{\text{update}} == 0$ **then**
17 Update channel information $h_{d,u}$ of the existing UE-IoT device pairs from previous time slot $t-1$.
18 **end**
19 // Communication Mode Selection:
20 Run Algorithm 1 to determine the IoT devices communicating using NOMA active transmission.
21 Run Algorithm 2 to determine the IoT devices communicating using backscattering and their associated UE relays.
22 **end**

On the other hand, the UE-IoT device scheduling requires (in the worst case) evaluating $\sum_{j=1}^{|\mathcal{U}|} j(|\mathcal{U}|-j)$ SINR values over the iterations in the while loop starting in Step 18. By evaluating the aforementioned series summation, we obtain the computational complexity of UE-IoT device scheduling as $O(|\mathcal{U}|^3)$. Hence, the overall computational complexity of Algorithm 2 is given by $O(|\mathcal{U}|^3+|\mathcal{U}|)=O(|\mathcal{U}|^3)$. Consequently, our proposed suboptimal algorithm for solving the communication mode selection problem has an overall computational complexity of $O(|\mathcal{D}|^3+|\mathcal{U}|^3)$, compared to $O(2^{|\mathcal{D}|^2|\mathcal{U}|^2})$ for obtaining the optimal solution.

D. Communication Mode Selection Algorithm

In this subsection, we present the overall communication mode selection algorithm. Algorithm 3 shows the steps of the communication mode selection for each time slot t. In Steps $2-7$, the BS updates the set of IoT devices by including the newly arriving IoT devices that have data to transmit and estimates their channel gain $h_{\text{BS},d}$. The BS also removes those IoT devices that were successfully served in the previous time slot via either active transmission or backscattering. Since most of the IoT devices are stationary, updating the channel gain for those IoT devices which have not been served in the previous time slots can be performed every $T_{\mathcal{D}}^{\text{update}}$ slots to reduce the channel estimation overhead. In Steps $8-13$, the BS updates the set of UE relays for the backscattering communication mode by including (or removing) the UE relays arriving (or leaving) the coverage area. Similarly, the channel gains of the existing active UE relays $h_{\text{BS},u}$ are updated every $T_{\mathcal{U}}^{\text{update}}$ slots. With new elements in the sets of IoT devices and UE relays, new potential UE-IoT device pairs are available for the backscattering mode as shown in Steps $14-18$. For these new pairs, the BS estimates the channel gain $h_{d,u}$. For the existing pairs, the BS updates the channel gain estimates every $T_{\mathcal{D},\mathcal{U}}^{\text{update}}$ slots. Subsequently, the BS has the necessary information to run Algorithm 1 for allocating subcarrier of active transmission for some IoT devices and considering the remaining IoT devices to use backscattering mode by running Algorithm 2 as shown in Steps $19-21$. Note that the IoT devices that are not served in time slot t are to be considered for communication mode selection in the following time slot $t+1$.

IV. Performance Evaluation

For performance evaluation, we consider a 100 m $\times$ 100 m coverage area that is served by a single BS, where 50 IoT devices and 25 UEs are placed uniformly (and the locations are varied in each simulation run). We assume flat Rayleigh fading channels. The total system bandwidth is divided into equal bandwidth subcarriers. The number of subcarriers considered for active transmission is set to 12, where each subcarrier has a bandwidth of 3.75 kHz, following the bandwidth of narrowband subcarriers in narrowband IoT systems [33]. In addition, one separate subcarrier of the same bandwidth is used for the backscattering communication mode. The distance-dependent path loss $PL(\text{distance})$ at carrier frequency $f_c = 900$ MHz is calculated by $PL(\text{distance}) = \frac{4\pi d_{\text{ref}} f_c^2}{(3\times 10^8)^2}(\frac{\text{distance}}{d_{\text{ref}}})^{\psi}$, where d_{ref} is the reference distance of 1 m and ψ is the path loss exponent that is set to 3.5. The distance takes into account the heights of BS, UEs, and IoT devices, which are 25 m, 1.5 m and 1.5 m, respectively [34]. We consider additive white Gaussian noise with power spectral density -174 dBm/Hz and a receiver noise figure of 5 dB and 7 dB at BS and UEs, respectively [34]. We set the transmit power of the BS P_{BS} to be 30 dBm. The transmit power of UEs P_u is equal to 23 dBm [35, p. 481]. The maximum transmit power for the IoT devices is 14 dBm. Similar to [36], [37], the SNR threshold for successful decoding at the BS and the UEs are set as $\gamma_{\text{BS}}^{(\text{th})} = \gamma_{\text{UE}}^{(\text{th})} = 2$. We also set $|\zeta_d| = 0.7$ [38].

We compare the connection density supported by the proposed communication mode selection scheme with schemes where only one communication technology is available for the IoT devices (either backscattering or active transmission). We also consider two variants of the suboptimal algorithm. The first variant of the suboptimal algorithm is to first solve the active transmission subproblem and then consider the non-scheduled devices for UE-IoT device pairing in the backscattering subproblem (as described in Section III). We denote this variant as suboptimal-TB. The second variant is to first solve the backscattering subproblem and then consider the non-scheduled devices for NOMA pairing in the active transmission subproblem. We denote this variant as suboptimal-BT.

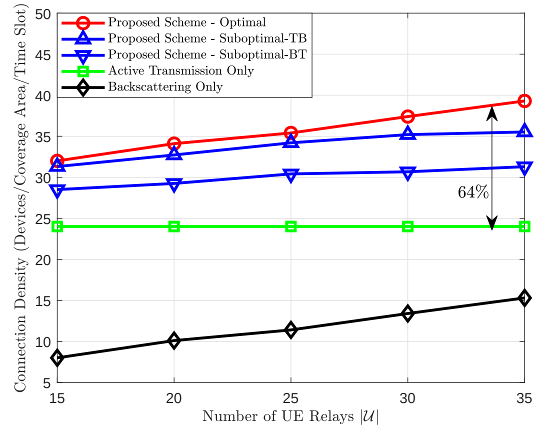

Fig. 2. Connection density versus the number of UE relays $|\mathcal{U}|$ with complete CSI ($P_{\text{BS}} = 30$ dBm, $|\mathcal{S}| = 12$ subcarriers, $\gamma_{\text{BS}}^{(\text{th})} = \gamma_{\text{UE}}^{(\text{th})} = 2$).

A. Connection Density with Complete CSI

In this subsection, we evaluate the connection density of our narrowband IoT system. The BS can obtain the CSI of all links in the network (the BS-UE links, BS-IoT device links, and UE-IoT device links), i.e., $|h_{m,n}|$ is known at the BS for all $m,\ n \in \{\text{BS}\} \cup \mathcal{U} \cup \mathcal{D}$.

Fig. 2 shows the impact of the number of UE relays on the connection density. With more UE relays available, more IoT devices can be associated with nearby UE relays and use backscattering for data transmission while satisfying the minimum SNR requirement. Thus, the connection density can be increased. We also note that the suboptimal algorithm described in Section III (i.e., suboptimal-TB) outperforms the other suboptimal variant suboptimal-BT. This indicates that forming NOMA pairs requires having as many potential IoT devices as possible that can use active transmission mode in order to find more pairs of IoT devices with sufficient difference in channel quality. Hence, solving the active transmission problem first in the suboptimal-TB algorithm provides more NOMA pairing options than the suboptimal-BT algorithm.

In Fig. 3, we show the impact of varying the number of active transmission subcarriers $|\mathcal{S}|$. As the number of subcarriers increases, more IoT devices can use active transmission with either OMA or NOMA. Consequently, a higher connection density can be achieved by both the optimal and suboptimal algorithms. The proposed communication mode selection scheme can increase the connection density by up to 65% compared to using active transmission only. On the other hand, Fig. 4 shows that increasing the minimum SNR threshold for successful data decoding at the BS or UE relays results in supporting a lower number of IoT devices.

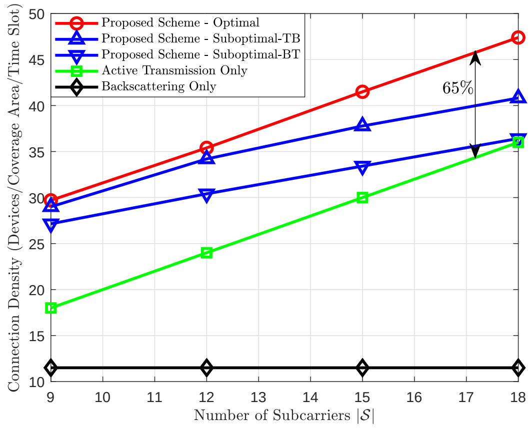

Fig. 3. Connection density versus the number of subcarriers $|\mathcal{S}|$ with complete CSI ($P_{\rm BS} = 30$ dBm, $|\mathcal{U}| = 25$ UEs, $\gamma_{\rm BS}^{\rm (th)} = \gamma_{\rm UE}^{\rm (th)} = 2$).

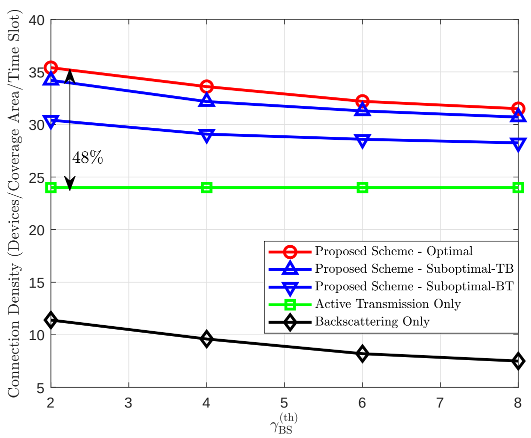

Fig. 4. Connection density versus the SNR decoding threshold $\gamma_{\rm BS}^{\rm (th)}$ with complete CSI ($\gamma_{\rm UE}^{\rm (th)} = \gamma_{\rm BS}^{\rm (th)}$, $P_{\rm BS} = 30$ dBm, $|\mathcal{S}| = 12$ subcarriers).

We also note that the proposed suboptimal-TB scheme achieves a close performance to the optimal solution, especially when the communication resources are limited (e.g., $|\mathcal{U}| \leq 30$). In particular, the difference in supported connection density by the optimal and suboptimal algorithms does not exceed 2 devices per coverage area per time slot for most of the simulation scenarios. However, the suboptimal algorithm always has the advantage of its lower computational complexity.

B. Connection Density with Partial CSI

In this subsection, we evaluate the connection density of a narrowband IoT system with partial knowledge of the CSI. In particular, we assume that the CSI of the BS-UE links and BS-IoT device links is known. However, the CSI of the UE-IoT device links is unknown due to the difficulty of estimating $\tilde{h}_{d,u}$. Given that the BS only obtains information about UE and IoT devices locations, we assume that $|h_{d,u}| = \sqrt{\ell_{d,u}}$ (i.e., $|\tilde{h}_{d,u}|^2 = 1$).

In Figs. 5, 6, and 7, we compare the performance of the proposed optimal and suboptimal algorithms with complete and partial CSI by varying the number of UE relays, number

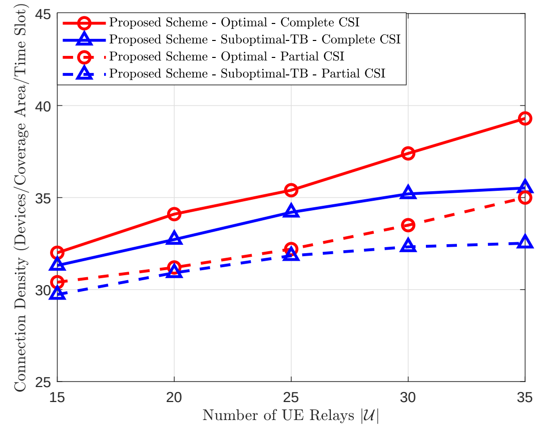

Fig. 5. Connection density versus the number of UE relays $|\mathcal{U}|$ with complete and partial CSI ($P_{\rm BS} = 30$ dBm, $|\mathcal{S}| = 12$ subcarriers, $\gamma_{\rm BS}^{\rm (th)} = \gamma_{\rm UE}^{\rm (th)} = 2$).

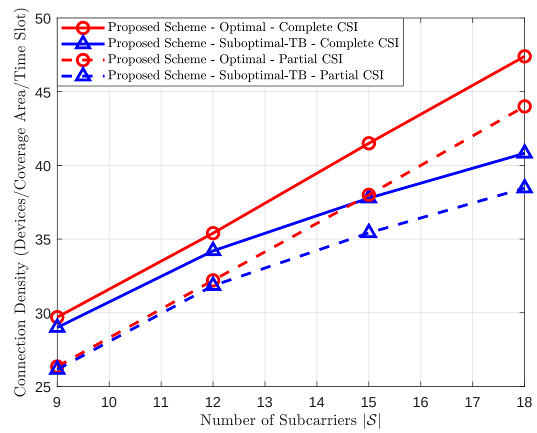

Fig. 6. Connection density versus the number of subcarriers $|\mathcal{S}|$ with complete and partial CSI ($P_{\rm BS} = 30$ dBm, $|\mathcal{U}| = 25$ UEs, $\gamma_{\rm BS}^{\rm (th)} = \gamma_{\rm UE}^{\rm (th)} = 2$).

of subcarriers, and SNR decoding threshold, respectively. The unavailability of the CSI of UE-IoT device links causes both algorithms to make incorrect UE-IoT pairing decisions for the backscattering mode. Hence, some UE-IoT device pairs fail to meet the minimum SNR requirements and the supported connection density is reduced. However, the performance of both algorithms is not significantly degraded due to the availability of partial CSI. The difference in supported connection density between the complete CSI and partial CSI cases with the optimal algorithm does not exceed 4 devices per coverage area per time slot. Moreover, the difference in supported connection density between the complete CSI and partial CSI cases with the suboptimal algorithm (suboptimal-TB) does not exceed 3 devices per coverage area per time slot.

C. Impact of Coverage Area

In this subsection, we study the impact of the BS transmit power and coverage area on the number of scheduled UE-IoT device pairs in the backscattering mode. We consider a network with 30 IoT devices and 30 UE relays. We deploy these IoT devices and UEs in three coverage areas of size 50 m $\times$ 50 m (high density), 100 m $\times$ 100 m (medium density),

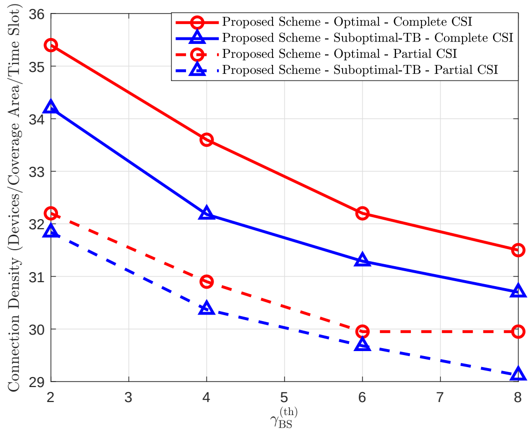

Fig. 7. Connection density versus the SNR decoding threshold $\gamma_{\text{BS}}^{(\text{th})}$ with complete and partial CSI ($\gamma_{\text{UE}}^{(\text{th})} = \gamma_{\text{BS}}^{(\text{th})}$, $P_{\text{BS}} = 30$ dBm, $|\mathcal{S}| = 12$ subcarriers).

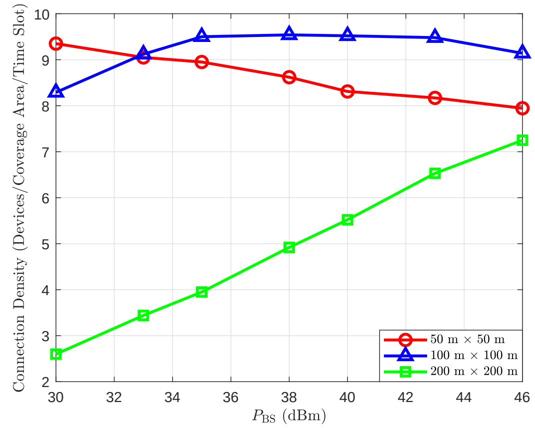

Fig. 8. Connection density versus the BS transmit power P_{BS} with complete CSI for different coverage areas ($|\mathcal{D}| = 30$ IoT devices, $|\mathcal{U}| = 30$ UEs, $\gamma_{\text{UE}}^{(\text{th})} = 2$).

200 m $\times$ 200 m (low density). The supported number of IoT devices via backscattering is depicted in Fig. 8. In the low density scenario (200 m $\times$ 200 m coverage area), increasing the BS transmit power enables associating more IoT devices to potential UE relays. This is due to using a higher power beacon signal which helps meeting the minimum SNR threshold for the backscattered signal at the UE. By increasing the density of the network (e.g., in 100 m $\times$ 100 m coverage area), increasing the BS transmit power beyond some limit (i.e., $P_{\text{BS}} > 38$ dBm) causes more interference among UE-IoT device pairs. Consequently, fewer UE-IoT device pairs can be scheduled for data transmission during the same time slot. In the high density scenario (50 m $\times$ 50 m coverage area), increasing the BS transmit power results in a consistent decrease in the supported connection density. Lower BS transmit power (i.e., $P_{\text{BS}} \leq 30$ dBm) should be used to increase the number of simultaneously scheduled UE-IoT device pairs.

D. Energy Efficiency Evaluation

In this subsection, we investigate the impact of the proposed communication mode selection scheme on the system energy efficiency. We consider a network consisting of $|\mathcal{D}| = 50$ IoT devices, $|\mathcal{U}| = 20$ UE relays, and $|\mathcal{S}| = 12$ subcarriers. We evaluate the energy efficiency for varying values of SNR decoding thresholds $\gamma_{\text{BS}}^{(\text{th})}$ and $\gamma_{\text{UE}}^{(\text{th})}$.

For active transmission mode, the consumed power of the IoT device is equal to the sum of circuitry power (which is set to be equal to 90 mW) and the transmit power [39]. We consider that each IoT device is equipped with a power amplifier that has an efficiency of 44%, i.e., the IoT device consumes $(1/0.44)P_d$ in order to transmit a signal with transmit power P_d [39]. To calculate the data rate in bps/Hz of each IoT device served using active transmission, we evaluate $R_d = \log_2(1+\gamma_d)$, where γ_d is the actual SNR based on the transmit power of the IoT device (evaluated by solving problem (7)), its assigned NOMA pair, and its decoding order. For IoT devices that are decoded first, $R_{d_1} = \log_2(1 + \frac{P_{d_1}|h_{\text{BS},d_1}^{(\text{tr})}|^2}{P_{d_2}|h_{\text{BS},d_2}^{(\text{tr})}|^2+\sigma_{\text{BS}}^2})$. For

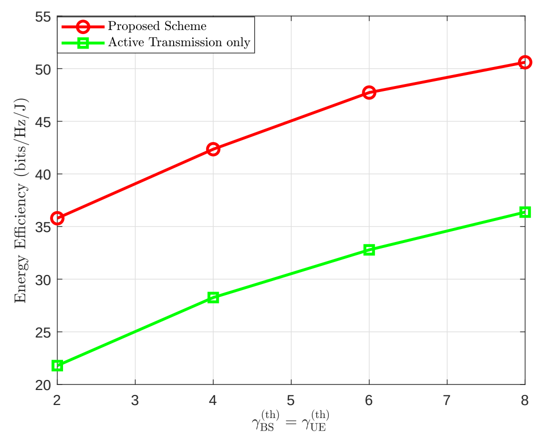

Fig. 9. Energy efficiency versus the SNR decoding threshold $\gamma_{\text{BS}}^{(\text{th})}$ with complete CSI ($\gamma_{\text{UE}}^{(\text{th})} = \gamma_{\text{BS}}^{(\text{th})}$, $P_{\text{BS}} = 30$ dBm).

IoT devices that are decoded second, the data rate R_{d_2} is given by $\log_2(1 + \frac{P_{d_2}|h_{\text{BS},d_2}^{(\text{tr})}|^2}{\sigma_{\text{BS}}^2})$.

On the other hand, backscattering IoT devices act as backscatter transmitters during communication with a power consumption of 7.2003 mW [6]. For an IoT device d associated with UE u, the achievable data rate R_d is evaluated by $\log_2(1 + \frac{z_{d,u}G_{d,u}}{\sum_{k\in\mathcal{D}\setminus\{d\}}\sum_{v\in\mathcal{U}\setminus\{u\}} z_{k,v}G_{k,u}+\sigma_u^2})$ which takes into account the interference caused by other scheduled UE-IoT device pairs.

We evaluate the energy efficiency of the system (in bits/Hz/J) as the ratio of the aggregate data rate of the served IoT devices to the aggregate power consumption of served IoT devices. The proposed communication mode selection scheme is compared with active transmission mode. Results in Fig. 9 show that our proposed scheme provides a higher energy efficiency than the active transmission mode.

V. Conclusion

In this paper, we proposed a communication mode selection scheme. In this scheme, each IoT can either use active transmission or backscattering for data transmission. UEs are utilized as relays to support the backscattering communication mode by receiving the backscattered signals from nearby IoT devices before forwarding the signals to the BS. This enables more IoT devices to use this energy-efficient communication technology. We formulated the communication mode selection as a connection density maximization problem. For the IoT devices using active transmission, two devices can share each subcarrier with power-domain NOMA. Meeting minimum SNR requirements is insured while consuming the minimum transmit power. On the other hand, for the IoT devices using backscattering, they are associated with UE relays. The maximum number of UE-IoT device pairs are scheduled to communicate in the same time slot while meeting the minimum SNR requirement for all the scheduled pairs. The formulated problem is a BIP problem. An algorithm with high computational complexity ($O(2^{|\mathcal{D}|^2|\mathcal{U}|^2})$) is required in order to solve this problem. Hence, we proposed a suboptimal algorithm by decomposing the problem into two subproblems that can be solved by bipartite matching and heuristic algorithms. The suboptimal algorithm achieved close performance to the optimal solution in the majority of simulation cases. In addition, the suboptimal algorithm has a polynomial computational complexity of $O(|\mathcal{D}|^3+|\mathcal{U}|^3)$. Simulation results showed that the proposed communication mode selection scheme enhanced the connection density of narrowband IoT systems by up to 64% when compared with using a single communication mode in a 100 m^2 coverage area when assuming the availability of complete CSI. To extend this work, we can consider enhancing the suboptimal algorithm to reduce the optimality gap when more UE relays are available in the system. We can also consider dynamic subcarrier allocation so that the IoT devices using different communication modes can share the same set of subcarriers in a flexible manner. In addition, we can develop incentive mechanisms for the UE relays using game-theoretic approaches. Furthermore, we can consider developing distributed algorithms for establishing ad hoc networks among the backscattering IoT devices and nearby UE relays, which can receive the backscattered data signals and forward them to the BS.

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