Single or Multiple Frames Content Delivery for Next-Generation Networks?

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Abstract—This paper addresses the four enabling technologies, namely multi-user sparse code multiple access (SCMA), content caching, energy harvesting, and physical layer security for proposing an energy and spectral efficient resource allocation algorithm for the access and backhaul links in heterogeneous cellular networks. Although each of the above mentioned issues could be a topic of research, in a real situation, we would face a complicated scenario where they should be considered jointly, and hence, our target is to consider these technologies jointly in a unified framework. Moreover, we propose two novel content delivery scenarios: 1) single frame content delivery (SFCD), and 2) multiple frames content delivery (MFCD), where the time duration of serving user requests is divided into several frames. In the first scenario, the requested content by each user is served over one frame. However, in the second scenario, the requested content by each user can be delivered over several frames. We formulate the resource allocation for the proposed scenarios as optimization problems where our main aim is to maximize the energy efficiency of access links subject to the transmit power and rate constraints of access and backhaul links, caching and energy harvesting constraints, and SCMA codebook allocation limitations. Due to the practical limitations, we assume that the channel state information values between eavesdroppers and base stations are uncertain and design the network for the worst case scenario. Since the corresponding optimization problems are mixed integer non-linear and nonconvex programming, NP-hard, and intractable, we propose an iterative algorithm based on the well-known alternate and successive convex approximation methods. In addition, the proposed algorithms are studied from the computational complexity, convergence, and performance perspectives. Moreover, the proposed caching scheme outperforms the existing traditional caching schemes like random caching and most popular caching. We also study the effect of joint and disjoint considerations of enabling technologies for the performance of next-generation networks. We also show that the proposed caching strategy, MFCD and joint solutions have 43%, 9.4% and %51.3 performance gain compared to no caching, SFCD and disjoint solutions, respectively.

Index Terms— Heterogeneous cellular networks, Content caching, Physical layer security, Energy harvesting, Imperfect CSI.

1 INTRODUCTION

1.1 Background and Motivation

Over recent years, the growth of high data rate of mobile traffic, energy, content storing, security, and limited knowledge of channels over mobile networks are the major challenges of network design and implementation. To tackle these issues and cope with the users’ requirements, the next-generation of wireless communications is introduced which uses multiple advanced techniques such as energy harvesting (EH), physical layer (PHY) security, new multiple access techniques, and content caching. Hence, all of these issues must be considered together and efficient joint radio resource allocation and content placement algorithms must be applied to provide high performance for the designed networks. However, devising efficient algorithms to handle all these issues is a challenging task, and to the best our knowledge, no research exists addressing all these issues together in a unified framework. Although each of the mentioned issues could be an interesting research topic, our main contribution is to study the joint effect of security, EH, content caching, and imperfect and limited channel knowledge in a unified joint access and backhaul links framework. In this regards, we develop a comprehensive model and mathematical representation, and design a robust resource allocation algorithm. Although the resulting optimization problem is complicated, effective optimization methods are used to achieve the solution. The outline of each issue, applicable solutions, and related works are explained in the sequel.

1.1.1 Growth of High Data Rate Mobile Traffic

Incredible growth in high data rate mobile applications requires high capacity in radio access and backhaul wireless links. However, the centralized nature of mobile network architectures cannot provide enough capacity on the wireless access and backhaul links to satisfy high demand for rich multimedia content. Heterogeneous network consisting of multiple low power radio access nodes and the traditional macrocell nodes, is a promising solution to improve coverage and to provide high capacity [1].

1.1.2 Content Caching

Multimedia services can be provided using recent advanced mobile communication technologies by new types of mobile devices such as smart phones and tablets. However, transferring the same content several times in a short period imposes capacity pressures on the network. To overcome this, content caching at the network edge has recently been emerged as a promising technique in next-generation networks. Caching in next-generation mobile networks also reduces the mobile traffic by eliminating the redundant traffic
of duplicate transmissions of the same content from servers. The deployment of content caching relevant to evolved packet core and radio access network (RAN) are studied in [2]. By caching, contents can be closer to the end-users, and backhaul traffic can be offloaded [3], [4] to the edge of the network. The authors in [5], [6] investigate caching the contents in RAN with the aim to store contents closer to users. The content caching in small-cell base stations is studied in [6], [7]. In [6], the authors reduce both the load and energy consumption of the backhaul links by caching the most popular contents at small base stations (SBSs). In [9], the authors consider two-tier heterogeneous wireless networks (HetNets) with hierarchical caching, where the most popular files are cached at SBSs while the less popular ones are cached at macro base stations (MBSs). The goal of [9] is to maximize network capacity with respect to the file transmission rate requirements by optimizing the cache sizes for MBSs and SBSs.

1.1.3 Energy Harvesting

The offer of high-rate services increases the energy consumption at receivers which degrades the battery life. Therefore, the trade-off between high-rate requirement and long battery life is required to achieve good performance. Energy harvesting has emerged as a promising approach to provide sustainable networks with the long-term sustainable operation of power supplies. In EH communication networks, nodes acquire energy from environmental energy sources including random motion and mechanical vibrations, light, acoustic, airflow, heat, RF radio waves [10], [11]. The design of novel transmission policies due to highly random and unpredictable nature of harvestable profile of the harvested energy is required.

1.1.4 New Multiple Access Techniques

Sparse code multiple access (SCMA) with near optimal spectral efficiency is a promising technique to improve capacity of wireless radio access [12]. This multiple-access technique that is based on non-orthogonal codebook assignment provides massive connectivity and improves spectral efficiency [12]–[14]. By performing an appropriate codebook assignment, a subcarrier in SCMA networks can be shared among multiple users. Joint codebook assignment and power allocation for SCMA is studied in [15]. The codebook assignment and power allocation is also investigated in [16]. The authors formulate energy-efficient transmission problem to maximize the network energy efficiency (EE) subject to system constraints.

1.1.5 Imperfect Channel State Information

In most previous works, the authors assume perfect channel state information (CSI) of all links for BSs. However, in practice, knowing of perfect CSI in BSs requires a huge amount of bandwidth for signalling through the feedback links which is not possible. Moreover, due to time varying channel, feedback delay, quantization error, and estimation errors, perfect CSI may not be available at transmitters. In this regard, some works aim to tackle the performance degradation caused by the limited and imperfect CSI [1], [17], [18]. In [17], the authors investigate the power and subcarrier allocation by the quantized CSI. It is assumed that the perfect CSI does not exist at transmitters and imperfect CSI can be achieved via limited rate feedback channels. In [1], joint power and subcarrier allocation is studied for the uplink of an orthogonal frequency-division multiple access (OFDMA) HetNet assuming imperfect CSI. In [18], a limited rate feedback scheme is considered to maximize the average achievable rate for decode-and-forward relay cooperative networks.

1.1.6 Security

The broadcast nature of wireless transmission makes security against eavesdropping a major challenge for the next generation wireless networks [19]. In this regards, physical layer security is a promising method to provide security in wireless networks [20], [21]. This technique explores the characteristics of the wireless channel to provide security for wireless transmission. In [22], the authors consider physical layer security for relay assisted networks with multiple eavesdroppers. They maximize the sum secrecy rate of network with respect to transmission power constraint for each transmitter via imperfect CSI. In [23], the authors investigate the benefits of three promising technologies, i.e., physical layer security, content caching, and EH in heterogeneous wireless networks.

1.1.7 Joint Backhaul and Access Resource Allocation

Joint resource allocation at backhaul and access links is investigated in [24] for heterogeneous networks. In [24], the full duplex self-backhauling capacity is used to simultaneously communicate over the backhaul and access links. In [25], joint access and backhaul links optimization is considered to minimize the total network power consumption. In [26], the authors study joint wireless backhaul and the access links resource allocation optimization. The goal is to maximize the sum rate subject to the backhaul and access constraints. Joint backhaul and access links optimization is considered in [27] for dense small cell networks. Joint resource allocation in access and backhaul links is considered for ultra dense networks in [28] where the goal is to maximize the throughput of the network under system constraints. In [29], the authors consider joint access and backhaul resource allocation for the admission control of service requests in wireless virtual network. The access and backhaul links optimizations are considered for small cells in the mmW frequency in [30].

1.2 Our Contributions

This paper addresses the above joint provisioning of resources between the wireless backhauls and access links by using multi-user SCMA (MU-SCMA) to improve the network energy efficiency. We consider secure communications in EH enabled SCMA downlink communications with imperfect channel knowledge. In our work, we combine and extend several techniques to improve performance of network and formulate an optimization problem with the aim of maximizing EE with respect to system constraints. There are several works which consider each of these topics separately. However, in a real situation, these issues should be considered jointly. To the best of our knowledge, none of
the existing works considered the above issues in a unified framework. The main contributions of this work are as follows:

- We provide a unified framework in which physical layer security, content caching, EH, and imperfect knowledge of channel information is considered jointly in the design of wireless communication networks.
- We consider SCMA as a non-orthogonal multiple access technology where the codebooks are allowed to be used several times among users which increases the spectral efficiency.
- We propose two novel scenarios for content delivery, namely single frame content delivery (SFCD), and multiple frames content delivery (MFCD). We compare the performance of the proposed delivery scenarios with each other for different system parameters. Due to the random energy arrivals in the EH based communication, there may not be enough energy to send the entire file within the desired frames. Therefore, the first scenario may interrupt sending the file. To overcome this difficulty, we can use the second scenario. There, due to the file transfer in multiple frames, the probability of interrupting will be very low. It should be noted that the second scenario can be suitable for applications with large file sizes.
- We consider the access and backhaul links jointly and formulate the resource allocation for the proposed scenarios as optimization problems whose objectives are to maximize the energy efficiency of the network while transmit power and rate constraints, EH constraints, codebook assignment constraints, as well as caching constraints should be satisfied.
- We provide mathematical frameworks for our proposed resource allocation problems where fractional programming, alternative optimization, and successive convex approximation methods are successfully applied to achieve solutions for the resource allocation optimization problems. We further study the convergence and the computational complexity of the proposed resource allocation algorithms.
- We evaluate and assess the performance of the proposed scheme for different values of the network parameters using numerical experiments.

The following notations is used in the paper: $|x|^+ = \max \{0, x\}$. $|S|$ denotes the cardinality of a set $S$. $[,]^\dagger$ represents the conjugate transpose. $||.|.$ denotes the Euclidean norm of a matrix/vector.

The rest of the paper is organized as follows. Section 2 defines the system model. Section 3 is dedicated to the optimization frameworks where the objectives and the constraints are explained. Section 4 describes the details of scheduling, power allocation algorithm, content placement, EH, codebook assignment, and subcarrier allocation. In Section 5, we provide the numerical analysis, and Section 7 concludes the paper.

2 System Model

Consider the downlink SCMA transmission of a wireless heterogeneous cellular network comprising of $O$ MBSs and $J$ SBSs in a two dimensional Euclidean plane $\mathbb{R}^2$, as shown in Fig. 1. Let us denote by $O = \{1, 2, \ldots, O\}$ the set of the MBSs and by $J = \{1, 2, \ldots, J\}$ the set of the SBSs. Each cache-capable BS, i.e., $b \in B = \{1, \ldots, B\} = O \cup J$ with size $B = |B|$, is connected to the core network via backhaul links which are wireless links. The paper assumes that there is no interference between the wireless backhaul and access links and these links are out-of-band. A set of total number of users, $U_b = \{1, 2, \ldots, U_b\}$ is served by BS $b$ with size $U_b = |U_b|$. The set of network users is $U = \bigcup_{b=1}^{B} U_b$. The system consists of $Q$ eavesdroppers which are indexed by $q \in Q = \{1, 2, \ldots, Q\}$ with size $Q = |Q|$. The total transmit bandwidth of the access, i.e., $BW$, is divided into $N$ subcarriers where the bandwidth of each subcarrier is $BW_n$ ($BW = N \times BW_n$). $K$ social media $\omega_k$, $k \in K = \{1, \ldots, K\}$, as the main traffic of internet contents, are requested by the users in the network. We assume that during the runtime of the network optimization process, user-BS association is fixed. The message passing algorithm (MPA) can be used to detect multiplexed signals on the same subcarriers \cite{32}. In our resource allocation framework, we consider two tasks: content caching and delivery resource allocations. The content caching task deals with determining which content should be cached in which storage. However, the delivery task deals with performing resource allocation such that the contents are delivered to the requesting users within serving time. We assume that the time is split into several superframes. We further assume that each super frame is divided into $F$ frames of duration $T$ seconds. throughout each super frame, the arriving users requests, which should be served over the next super frame, are gathered by the network control system. We emphasize that our proposed content caching and resource allocation algorithms are run for each super frame. Throughout the network run time, the network monitors the file requests and estimate the content distribution (content popularity). At the beginning of each super frame, if a change in the statistics of the contents popularity is detected, joint content caching and radio resource allocation is performed, and otherwise, only radio resource allocation is performed. Note that the proposed resource allocation problem is solved at the beginning of each super frame, and hence, the information about the CSIs and energy harvesting profile over all $F$ frames of the considered supper frame are required and should be known in advanced. With such assumption, we rely on the off-line approach which is common in the context of energy

1. Point-to-multipoint (P2M) technologies are considered as backhaul networks for small cell which is an effective way of sharing the backhaul resource between several BSs. PMP backhaul has high spectral efficiency, and speed and flexibility of deployment, and have been successfully deployed in the Middle East, Africa and in Europe by major operators \cite{31}.
harvesting [33, 34]. The proposed transmission structure is shown in Fig. 2.

Let $s = \{s_{bu}^m\}$ denote the codebook assignment at BS $b$ at frame $t$ where $s_{bu}^m$ is an indicator variable that is 1 if codebook $m$ is assigned to user $u$ at BS $b$ at frame $t$ and 0 otherwise. Furthermore, let $p = \{p_{bu}^m\}$ denote the allocated transmit power vector with $p_{bu}^m$ representing the transmit power for user $u$ at BS $b$ at frame $t$ on codebook $m$. Thus, the total transmit power of BS $b$ at frame $t$ is $\sum_{u \in U_b} \sum_{m \in M} s_{bu}^m p_{bu}^m, \forall b \in B, t \in \mathcal{F}$. To transmit the codewords to the designated users, the transmit power $p$ is finally allocated on the corresponding subcarriers. However, different from OFDMA based networks, the transmit power $p_{bu}^m$ is allocated on subcarrier $n$ according to a given proportion $\eta_{nm}$, which is determined by the codebook design ($0 < \eta_{nm} < 1$ when $c_{nm} = 1$ and $\eta_{nm} = 0$ when $c_{nm} = 0$ [12]). Therefore, the signal-to-interference-plus-noise ratio (SINR) of user $u$ in BS $b$ when using codebook $m$ can be expressed as follows:

$$\gamma_{bu}^m = \frac{\sum_{n \in N} \eta_{nm} s_{bu}^m p_{bu}^m g_{bu}^m}{I_{bu}^m + (\sigma_a^u)^2},$$

(1) where $I_{bu}^m = \sum_{b \in B \setminus \{b\}} \sum_{a \in U_b} \sum_{n \in N} \eta_{nm} s_{bu}^m p_{ba}^m g_{ba}^m$ and $g_{bu}^m$ denotes the channel power gain between BS $b$ and user $u$ on subcarrier $n$ at time $t$. $(\sigma_a^u)^2$ is the noise power on subcarrier $n$ at user $u$. Each of the subcarriers can be assumed to undergo a block-fading, and hence, the channel coefficients are kept constant within each frame. The achievable rate for the $u^{th}$ user in BS $b$ at frame $t$ on codebook $m$ is given by $R_{bu}^{b,m} = \log_2 (1 + \gamma_{bu}^m)$.

We assume that the eavesdroppers only wiretap the access link. Therefore, the SINR of eavesdropper $q$ in BS $b$ when using codebook $m$ can be expressed as:

$$\gamma_{buq}^{b,m} = \frac{\sum_{n \in N} \eta_{nm} s_{bu}^m p_{bu}^m g_{bu}^m}{\hat{g}_{bu}^m + (\sigma_a^q)^2},$$

(2) where $\hat{g}_{bu}^m = \sum_{b \in B \setminus \{b\}} \sum_{a \in U_b} \sum_{n \in N} \eta_{nm} s_{bu}^m p_{ba}^m h_{ba}^m g_{ba}^m$ and $h_{ba}^m$ denotes the channel power gain between BS $b$ and eavesdropper $q$ on subcarrier $n$. $(\sigma_a^q)^2$ is the noise power on subcarrier $n$ at eavesdropper $q$. The achievable rate for the $q^{th}$ eavesdropper in BS $b$ at frame $t$ is evaluated by $R_{buq} = \log_2 (1 + \gamma_{buq}^{b,m})$. The achievable secrecy access rate for non-colluding eavesdroppers and the $u^{th}$ user in BS $b$ at frame $t$ on codebook $m$ is expressed as [35].

$$R_{bu}^{s,m} = \max_{q \in Q} R_{buq}^{E,m} + 1. \tag{3}$$

3 THE OPTIMIZATION FRAMEWORK
In this section, we provide the design objective and a characterization of the constraints that must be satisfied by content caching, EH, codebook assignment, and power allocations.

3.1 System Constraints
3.1.1 Content Caching Constraints
Let the finite size of cache memory at the $u^{th}$ BS is denoted by $V_b$. If the requested file $k$ by user $u$ exists in the cache, then the file is sent to the user immediately. This event is referred as a cache hit. However, if file $k$ does not exist in the cache, then the request is forwarded to the core network via backhaul, then downloaded file $k$ from the core network via backhaul is forwarded to the user. The size of the social media, $\alpha_k, k \in \mathcal{K}$ is assumed to be Log-Normal distributed with parameters $\mu$ and $\kappa$ [36]. As the total cached media should not exceed the finite size of cache memory at BS $b$, we have

$$\sum_{k \in \mathcal{K}} \theta_{bk} \alpha_k \leq V_b, \forall b \in B, \tag{4}$$

where $\theta_{bk}$ is a binary indicator declaring whether social media $\omega_k$ is cached at BS $b$. 

Fig. 1. The proposed wireless network with macro-BSs, small BSs, users, and eavesdroppers.
3.1.2 Content Delivery

The content delivery consists of two phases: 1) a cache placement phase, and 2) a content delivery phase. In the cache placement phase, the cache content is determined at each BS, and in the content delivery phase, the requested files are delivered to users over wireless channels. In this paper, two new delivery scenarios are considered for content delivery phase. In the first scenario, the user’s requested file \( k \) with size \( \alpha_k \) is sent in a single frame, while in the second scenario the user’s requested file \( k \) is divided into several parts with sizes \( \{\beta_k^t\} \), \( \forall t, k \), which are sent over several frames. The scenarios are shown in Fig. 2. To ensure that all parts of each file are transmitted to user, the following constraint should be satisfied

\[
\sum \beta_k^t = \alpha_k, \forall k. \tag{5}
\]

3.1.3 Access and Backhaul Links Constraints

Let \( \upsilon_{ku} \) denote whether user \( u \) needs \( \omega_k \). The backhaul traffic constraint for BS \( b \) for the SFCD scenario is written as follows

\[
\sum_{k \in K} \sum_{u \in U_b} \sum_{m \in M} s_{bu}^{mt} (1 - \theta_{bk}), \min \left\{ \sum_{u \in U_b} \upsilon_{ku}, 1 \right\} \alpha_k, \forall k. \tag{6}
\]

where the left hand side term of (6) is the backhaul traffic for BS \( b \) and the right hand side term of (6) is backhaul traffic capacity, which must be greater than the backhaul traffic for each BS. The backhaul link is a simple P2M link with OFDMA technology. \( \zeta_{bk} \in \{0, 1\} \) denotes whether BS \( b \) uses subcarrier \( n \). For the MFCD scenario, \( \alpha_k \) in (6) is replaced by \( \beta_k^t \) as follows

\[
\sum_{k \in K} \sum_{u \in U_b} \sum_{m \in M} \sum_{t \in T} s_{bu}^{mt} (1 - \theta_{bk}), \min \left\{ \sum_{u \in U_b} \upsilon_{ku}, 1 \right\} \beta_k^t \leq (7)
\]

\[
T \sum_{n \in N} \zeta_{bn} \tilde{R}_b^{nt}, \forall t \in F, b \in B. \tag{8}
\]

Fig. 2. SFCD and MFCF transmission structure.

3.1.4 Power Allocation Constraints

To determine the constraints that must be satisfied by any feasible power allocation, let \( p_{bu}^{mt} \) and \( \tilde{p}_b^{nt} \) denote the power
allocated to link the $b^{th}$ BS-the $u^{th}$ user at time frame $t$ on codebook $m$ and to link core network-the $b^{th}$ BS at frame $t$. The elements of $p_{bu}^{mt}$ and $\tilde{p}_{bu}^{mt}$ must satisfy the followings:

$$p_{bu}^{mt} \geq 0, \forall b \in B, u \in U_b, m \in M, t \in F,$$  

(11)

$$\tilde{p}_{bu}^{mt} \geq 0, \forall b \in B, n \in N, t \in F.$$  

(12)

In a practical network, a BS has a power budget, $P_{\text{total},b}$, which bounds the total power allocated by the BS. For the SFCD scenario, we have $P_{\text{total},b} = \rho_{\text{b}}$, where $\rho_{\text{b}}$ denotes the unit amount of energy harvested at each BS. Therefore, $E_{b}^{t}$ can be written in recursive form as:

$$E_{b}^{t+1} = \min \left( E_{b}^{t} - T \sum_{m \in M, u \in U_b} c_{bu}^{mt} p_{bu}^{mt} + E_{b}^{\text{max}}, E_{b}^{\text{max}} \right),$$  

(13)

\[ \forall b \in B, t \in F, \]

where $\tilde{E}_{b}^{t}$ denotes the amount of energy harvested during the $t^{th}$ frame at the $b^{th}$ BS. The energy arrival takes place as a Poisson arrival process with mean $\Gamma_{b}$ [37], [38]. The unit amount of energy harvested at each BS is denoted by $\rho_{b}$, which depends on the EH capabilities of each BS. Therefore, $E_{b}^{t} = \omega_{b}^{t} \rho_{b}$, where $\omega_{b}^{t}$ is the number of arrivals within $T$ with a mean value of $\Gamma_{b}T$. In designing optimal transmission policies for EH communication systems, there are main constraints referred to energy consumption causality constraints, which state that the energy packets which do not arrive yet, cannot be used by a source. These constraints can be expressed as:

$$\sum_{t=1}^{f} \sum_{m \in M} \sum_{u \in U_b} s_{bu}^{mt} p_{bu}^{mt} \leq \frac{1}{T} \sum_{t=1}^{f} E_{b}^{t}, \forall b \in B, f \in F.$$  

(15)

If battery capacity is not enough to store the newly arrived energy packet, the energy will be wasted at the beginning of a transmission interval. By considering the following energy overflow constraint on our problem, we avoid this battery overflow by enforcing the following constraint:

$$\sum_{t=1}^{f+1} E_{b}^{t} - T \sum_{t=1}^{f} \sum_{m \in M} \sum_{u \in U_b} s_{bu}^{mt} p_{bu}^{mt} \leq E_{b}^{\text{max}}, \forall b \in B, f \in F.$$  

(16)

### 3.1.5 EH Constraints

We assume that the $b^{th}$ BS is connected to a rechargeable battery with capacity $E_{b}^{\text{max}}$, and obtains its power supply through an EH renewable sources such as solar. The renewable sources are used to charge batteries during the day. $E_{b}^{t} \in [0, E_{b}^{\text{max}}]$ is defined as the energy remaining in the battery at the start of the $t^{th}$ frame. Then $E_{b}^{t}$ can be written in recursive form as:

$$E_{b}^{t+1} = \min \left( E_{b}^{t} - T \sum_{m \in M, u \in U_b} c_{bu}^{mt} p_{bu}^{mt} + E_{b}^{\text{max}}, E_{b}^{\text{max}} \right),$$  

(13)

where $\tilde{E}_{b}^{t}$ denotes the amount of energy harvested during the $t^{th}$ frame at the $b^{th}$ BS. The energy arrival takes place as a Poisson arrival process with mean $\Gamma_{b}$ [37], [38]. The unit amount of energy harvested at each BS is denoted by $\rho_{b}$, which depends on the EH capabilities of each BS. Therefore, $E_{b}^{t} = \omega_{b}^{t} \rho_{b}$, where $\omega_{b}^{t}$ is the number of arrivals within $T$ with a mean value of $\Gamma_{b}T$. In designing optimal transmission policies for EH communication systems, there are main constraints referred to energy consumption causality constraints, which state that the energy packets which do not arrive yet, cannot be used by a source. These constraints can be expressed as:

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(15)

If battery capacity is not enough to store the newly arrived energy packet, the energy will be wasted at the beginning of a transmission interval. By considering the following energy overflow constraint on our problem, we avoid this battery overflow by enforcing the following constraint:

$$\sum_{t=1}^{f+1} E_{b}^{t} - T \sum_{t=1}^{f} \sum_{m \in M} \sum_{u \in U_b} s_{bu}^{mt} p_{bu}^{mt} \leq E_{b}^{\text{max}}, \forall b \in B, f \in F.$$  

(16)

### 3.1.6 Scheduling Constraints

In order to improve the detection performance, we should use the codebooks which have less subcarriers in common. This means that, it must be guaranteed that each subcarrier cannot be reused more than a certain value $D$, i.e., the maximum number of differentiable constellations generated by the codebook-specific constellation function, as follows:

$$\sum_{b \in B} \sum_{u \in U_b} \sum_{m \in M} c_{nm} s_{bu}^{mt} \leq D, \forall n \in N, t \in F.$$  

(17)

In addition, [18], [19], and [20] together denote that codebooks are exclusively allocated among users of each BS. For the SFCD scenario, we have

$$\sum_{m \in M} \sum_{t \in F} \sum_{u \in U_b} s_{bu}^{mt} \leq 1, \forall b \in B,$$  

(18)

and for the MFCD scenario, we have

$$\sum_{m \in M} \sum_{t \in F} \sum_{u \in U_b} s_{bu}^{mt} \leq 1, \forall b \in B, t \in F,$$  

(19)

$$s_{bu}^{mt} \in \{0, 1\}, \forall b \in B, u \in U_b, m \in M, t \in F.$$  

(20)

### 3.1.7 Worst Case Channel Uncertainty Model

For the channels between the $b^{th}$ BS and the $q^{th}$ eavesdropper, only the estimated value $\tilde{h}_{bq}^{mt}$ is available at the $b^{th}$ BS. We define the channel error as $e_{h_{bq}^{mt}} = |h_{bq}^{mt} - \tilde{h}_{bq}^{mt}|$, and we assume that the channels mismatches are bounded as follows:

$$e_{h_{bq}^{mt}} \leq \varepsilon_{h_{bq}^{mt}}, \forall b, q \in Q, n \in N, t \in F,$$  

(21)

where $\varepsilon_{h_{bq}^{mt}}$ is known constant. Hence the actual channel power gain value lies in the region $h_{bq}^{mt} \in \mathcal{H}_{bq}^{mt} = [h_{bq}^{mt} - \varepsilon_{h_{bq}^{mt}} h_{bq}^{mt} + \varepsilon_{h_{bq}^{mt}}]$ [39].

### 3.2 The Optimization Problem

We formulate the utility maximization problem with power allocation, codebook assignment, and content caching subject to energy causality and power budget constraints at each BS for the SFCD scenario as:

$$\max_{\mathbf{p}, \mathbf{s}, \mathbf{b}, \mathbf{h} \in \mathcal{H}} \min_{\mathbf{q}, \mathbf{h} \in \mathcal{H}} \Xi_{\text{IEEE}}(\mathbf{p}, \mathbf{s}),$$  

(22)

s.t. [4], [9], [11] - [18], [20], [21],

$$\Xi_{\text{IEEE}}(\mathbf{p}, \mathbf{s}) = \sum_{m \in M} \sum_{t \in F} \sum_{u \in U} \sum_{b \in B} s_{bu}^{mt} p_{bu}^{mt} / \sum_{m \in M} \sum_{t \in F} \sum_{u \in U} \sum_{b \in B} s_{bu}^{mt} p_{bu}^{mt},$$

$$h = [h_{bq}^{11}, \ldots, h_{bq}^{f}],$$

$$\mathcal{H} = \{h_{bq}^{11}, \ldots, h_{bq}^{f}\},$$

$$\mathcal{H}_{bq}^{F} = \mathcal{H}_{bq}^{11} \times \ldots \times \mathcal{H}_{bq}^{f}.$$  

Note that for the MFCD scenario, constraint [5] is added to the optimization problem [22]. We also replace [6], [9], and [18] by [7], [10], and [19], respectively. It should also be noted that in the second scenario, $\beta$ is itself an optimization variable that must be obtained in the optimization problem. The optimization problem [22] consisting of non-convex objective function and both integer and continuous variables. Hence, it is mixed-integer nonlinear programming (MINLP), non-convex, intractable and NP-hard problem [40].
The optimization problem \( (22) \) is NP-hard.

Proof. Please see Appendix A.

It is very difficult to find the global optimal solution within polynomial time. Hence, the available methods to solve convex optimization problem can not be applied directly. To solve this problem, an iterative algorithm based on the well-known and well-proven alternating, Dinkelbach and successive convex approximation methods is proposed where in each iteration, the main problem is decoupled into several sub-problems subject to some optimization variables.

4 PROPOSED SOLUTION

The difficulty of solving the problem \( (22) \) arises from the nonconvexity of both the objective function and feasible domain. As far as we know, there is no standard method to solve such a nonconvex optimization problem. In this section, some optimization methods such as alternative optimization, fractional programming, and difference-of-two-concave-functions (DC) programming, are jointly applied to solve the primal problem by transforming it into simple subproblems step by step. To facilitate solving \( (22) \), an alternate optimization method is adopted to solve a multilevel hierarchical problem which consists of the several subproblems. The core idea of the alternate optimization is that only one of the optimization parameters is optimized in each step while others are fixed. When each parameter is given, the resulting subproblem can be reformulated as the form of DC problem and solved by DC programming. Moreover, a sequential convex program is finally solved by convex optimization methods at each iteration of the DC programming. In this section, we propose a solution for the SCFCD scenario which is suitable for MFCD, too. The transformation process for solving this problem mainly consists of the following steps: I. Transformation of the primal problem: By using the epigraph method, the inner maximization in the objective function in \( (23) \) can be simplified and the secondary problem can be naturally derived. II. Alternate optimization over some variables: In this step, the alternate optimization method is adopted to cope with the nonconvexity of the resulting parametrized secondary problems which is further rewritten as five subproblems, namely, access power allocation, access code allocation, backhaul power allocation, backhaul subcarrier allocation, content placement, and channel uncertainty. III. DC programming for the nonconvex constraint elimination: In this step, we reformulate the nonconvex constraint \( (23) \) as a canonical DC programming which can be solved by iteratively solving a series of sequential convex constraints. Finally, these convex constraints can be solved by convex programming. IV. Fractional programming: Applying fractional programming, the parameterized secondary subproblem is solved with a given parameter in each iteration.

4.1 Transformation of the primal problem

For simplifying \( (22) \), we herein introduce auxiliary variables \( \varphi = \{ \varphi_{bu} \in \mathbb{R} \} \). Additionally, we can rewrite \( (22) \) equivalently as

\[
\begin{align*}
\max_{p, \hat{p}, s, \theta, \zeta, \varphi, \mathbf{h}} & \min_{p, \hat{p}, s, \theta, \zeta, \varphi, \mathbf{h}} A, \\
\text{s.t.} & \sum_{k \in \mathcal{K}} \sum_{m \in \mathcal{M}} s_{mt}^{bu} u_{ku} a_k \leq \sum_{m \in \mathcal{M}} \max \left\{ R_{bu}^D^{D,mt} - \varphi_{bu}, 0 \right\}, \\
& \forall t \in \mathcal{F}, b \in \mathcal{B}, u \in \mathcal{U}_b, \quad (23a)
\end{align*}
\]

where \( A = \sum_{m \in \mathcal{M}} \sum_{t \in \mathcal{F}} \sum_{b \in \mathcal{B}} \sum_{u \in \mathcal{U}_b} \max \left\{ R_{bu}^{D,mt} - \varphi_{bu}, 0 \right\} \). To solve the optimization problem \( (23) \), we should further transform it. We first rewrite \( \max \left\{ R_{bu}^{D,mt} - \varphi_{bu}, 0 \right\} \) as [41]:

\[
\begin{align*}
\max \left\{ R_{bu}^{D,mt} - \varphi_{bu}, 0 \right\} &= \max \left\{ -R_{bu}^{D,mt} - \varphi_{bu}, 0 - R_{bu}^{D,mt} \right\} + R_{bu}^{D,mt},
\end{align*}
\]

where

\[
\begin{align*}
R_{bu}^{D,mt} &= \log_2 \left( \sum_{b \in \mathcal{B}, u \in \mathcal{U}_b} \sum_{n \in \mathcal{N}} \left( \eta_{nm} s_{mt}^{mt} p_{bu} g_{bu} + (\sigma_u^2) \right) \right), \quad (24)
\end{align*}
\]

By introducing auxiliary variables \( \delta = \{ \delta_{bu} \in \mathbb{R} \} \), \( (23) \) is equivalently reformulated as [41]

\[
\begin{align*}
\max_{p, \hat{p}, s, \theta, \zeta, \varphi, \mathbf{h}} & \min_{p, \hat{p}, s, \theta, \zeta, \varphi, \mathbf{h}} \Theta(p, \hat{p}, s, \theta, \zeta, \varphi, \mathbf{h}), \\
\text{s.t.} & \sum_{k \in \mathcal{K}} \sum_{m \in \mathcal{M}} s_{mt}^{bu} u_{ku} a_k \leq \sum_{m \in \mathcal{M}} \left( \zeta_{sub} + R_{bu}^{D,mt} \right), \\
& \forall t \in \mathcal{F}, b \in \mathcal{B}, u \in \mathcal{U}_b, \quad (26a)
\end{align*}
\]

where

\[
\begin{align*}
\Theta(p, \hat{p}, s, \theta, \zeta, \varphi, \mathbf{h}) &= \sum_{m \in \mathcal{M}} \sum_{t \in \mathcal{F}} \sum_{b \in \mathcal{B}} \sum_{u \in \mathcal{U}_b} \left( \sum_{k \in \mathcal{K}} \sum_{m \in \mathcal{M}} s_{mt}^{bu} u_{ku} a_k \right) \zeta_{sub} + R_{bu}^{D,mt} \right) \\
&= \sum_{m \in \mathcal{M}} \sum_{t \in \mathcal{F}} \sum_{b \in \mathcal{B}} \sum_{u \in \mathcal{U}_b} \left( \sum_{k \in \mathcal{K}} \sum_{m \in \mathcal{M}} s_{mt}^{bu} u_{ku} a_k \right)
\end{align*}
\]

4.2 Alternate optimization over optimization variables

Due to the combined non-convexity of both objective function and the constraint with respect to optimization parameters, the optimization problem \( (22) \) is difficult to solve. According to alternate optimization method, we can always optimize a function by first optimizing over some of the variables, and then optimizing over the remaining ones. For convenience, the feasible domain of \( (22) \) is denoted by \( \mathbb{D} \) as \( \mathbb{D} = \{(p, \hat{p}, s, \theta, \zeta, \varphi, e_h) : \quad [4, 6, 9, 21]\} \). For fixed \( p, \hat{p}, s, \theta, \zeta, \varphi, e_h \)-section of the feasible domain of \( \mathbb{D} \), i.e., \( \mathbb{D}_{eh} \), is defined as \( \mathbb{D}_{eh} = \{e_h) : (p, \hat{p}, s, \theta, \zeta, \varphi, e_h) \in \mathbb{D}\} \). Likewise, for fixed \( p, \hat{p}, s, \theta, \zeta, \varphi, e_h \)-section of the feasible domain of \( \mathbb{D} \), i.e., \( \mathbb{D}_{p} \), is defined as \( \mathbb{D}_{p} = \{(p, \hat{p}, s, \theta, \zeta, \varphi, e_h) \in \mathbb{D}\} \). Similarly, for fixed \( p, \hat{p}, s, \theta, \zeta, \varphi, e_h \)-section of the feasible domain
of \( \mathbb{D} \), i.e., \( \mathbb{D}_n \), is defined as \( \mathbb{D}_n \triangleq \{ s : (p, \tilde{p}, s, \theta, \zeta, e_h) \in \mathbb{D} \} \). In the same way, for fixed \( p, s, \theta, e_h, \tilde{p} \times \zeta \)-section of the feasible domain of \( \mathbb{D} \), i.e., \( \mathbb{D}_p \times \zeta \), is defined as \( \mathbb{D}_p \times \zeta \triangleq \{ \tilde{p}, \zeta : (p, \tilde{p}, s, \theta, \zeta, e_h) \in \mathbb{D} \} \). Correspondingly, for fixed \( p, s, \theta, e_h, \tilde{p} \times \zeta \)-section of the feasible domain of \( \mathbb{D} \), i.e., \( \mathbb{D}_p \times \zeta \), is defined as \( \mathbb{D}_p \triangleq \{ (p, \tilde{p}, s, \theta, \zeta, e_h) \in \mathbb{D} \} \). Finally, the alternate optimization is used to solve the following hierarchical five-level optimization subproblem:

\[
\max_{p, p_\theta, s, \theta, \varphi, \epsilon_h} \ominus \Theta(p, p_\theta, s, \theta, \varphi, \epsilon_h).
\]  

(27)

In conclusion, the subproblems can be solved sequentially at each iteration of alternate optimization. In the first optimization subproblem, we find \( e_h \) for a given \( p, s, \varphi, \) and \( \delta \):

\[
\min_{e_h \in \mathbb{D}_e} \Theta(p, p_\theta, s, \theta, \zeta, \varphi, \epsilon_h).
\]  

(28)

where \( \vartheta \) is the iteration number of alternate optimization algorithm. By defining the solution of \( \Theta(p, p_\theta, s, \theta, \zeta, \varphi, \epsilon_h) \) as \( e_h^{\vartheta+1} \), the second level subproblem is solved to find \( \theta \) with a given \( p, s, \varphi, \) and \( \delta \):

\[
\max_{\theta \in \mathbb{D}_\theta} \Theta(p, p_\theta, s, \theta, \zeta, \varphi, \epsilon_h).
\]  

(29)

Similarly, by defining the solution of \( \Theta(p, p_\theta, s, \theta, \zeta, \varphi, \epsilon_h) \) as \( e_h^{\vartheta+1} \), the third level subproblem is solved to find \( \zeta \) and \( \tilde{p} \) with a given \( p, s, \varphi, \) and \( \delta \):

\[
\max_{\rho, \rho_\varphi} \Theta(p, p_\theta, s, \theta, \zeta, \varphi, \epsilon_h).
\]  

(30)

Correspondingly, by defining the solution of \( \Theta(p, p_\theta, s, \theta, \zeta, \varphi, \epsilon_h) \) as \( p_\varphi^{\vartheta+1} \) and \( \zeta^{\vartheta+1} \), the fourth level subproblem is solved to find \( s \) with a given \( p, \varphi, \) and \( \delta \):

\[
\max_{s \in \mathbb{D}_s} \Theta(p, p_\theta, s, \theta, \zeta, \varphi, \epsilon_h).
\]  

(31)

Finally, by defining the solution of \( \Theta(p, p_\theta, s, \theta, \zeta, \varphi, \epsilon_h) \) as \( s^{\vartheta+1} \), the fifth level subproblem is solved to find \( p, \varphi, \theta \) with a given \( s, \varphi, \) and \( \delta \):

\[
\max_{p, \varphi, \theta} \Theta(p, p_\theta, s, \theta, \zeta, \varphi, \epsilon_h).
\]  

(32)

Let \( (p, p_\theta, s, \theta, \zeta, e_h) \) denote the obtained solution at the \( \vartheta \)-th iteration, which should be used for the \( \vartheta+1 \)-th iteration. With a convergence threshold \( \epsilon_1 \), the stop condition of alternate optimization algorithm is then given by

\[
| \Theta(p, p_\theta, s, \theta, \zeta, \epsilon_1) - \Theta(p_{\vartheta+1}, p_{\vartheta+1}, s_{\vartheta+1}, \theta_{\vartheta+1}, \zeta_{\vartheta+1}, \varphi_{\vartheta+1}, e_h_{\vartheta+1}) | \leq \epsilon_1.
\]  

(33)

We can also present a maximum allowed number \( \Psi_1 \) for \( \vartheta_1 \). Alternately optimization algorithm is illustrated in Table. \( \square \) Furthermore, the following Theorem \( \square \) can verify the convergence of the alternate optimization algorithm.

**Theorem 1.** If \( \Theta(p, p_\theta, s, \theta, \zeta, \epsilon_1) \) are solvable, in each iteration, the sequence of each solution, i.e., \( \{ \Theta(p, p_\theta, s, \vartheta, \zeta, \epsilon_1) \} \), is monotonically decreasing.

**Proof.** Please see Appendix \( \square \)

### 4.2.1 Channel Uncertainty Problem

For minimizing the worst-case problem over \( \mathbb{H} \) in \( (28) \), we solve the following problem for each \( t, b, u, m, \) and \( q \):

\[
\max_{h^{nt}_{bq} \in \mathcal{H}^{nt}_{bq}} R^{nt}_{bq} \equiv \max_{h^{nt}_{bq} \in \mathcal{H}^{nt}_{bq}} \sum_{n \in \mathcal{N}} \eta_{nm}s^{nt}_{bu}p^{nt}_{bu}h^{nt}_{bq} \tag{34}
\]

We can rewrite \( (34) \) as follows:

\[
\max_{h^{nt}_{bq} \in \mathcal{H}^{nt}_{bq}} \left( \epsilon^{nt}_{bq} \right)^{\text{T}} h^{nt}_{bq} + \left( \sigma^n \right)^{2}, \tag{35a}
\]

\[
\begin{aligned}
&\text{s.t.} & h^{nt}_{bq} &\leq h^{nt}_{bq} + \varepsilon h^{nt}_{bq}, &\forall b, q, u, n \tag{35b}
& & h^{nt}_{bq} - \varepsilon h^{nt}_{bq} &\leq h^{nt}_{bq}, &\forall b, q, u, n \tag{35c}
\end{aligned}
\]

where \( \epsilon^{nt}_{bq} \) is a vector of the same dimension as \( h^{nt}_{bq} \) with all zero entry except for \( \epsilon^{nt}_{bq} = \eta_{nm}s^{nt}_{bu}p^{nt}_{bu}, \forall n, b \) and \( \epsilon^{nt}_{bq} \) is a vector of the same dimension as \( h^{nt}_{bq} \) with \( \epsilon^{nt}_{bq} = \sum_{u \in \mathcal{U}} \eta_{nm}s^{nt}_{bu}p^{nt}_{bu}, \forall b, q \neq q, n, \) and \( \epsilon^{nt}_{bq} = 0 \) for all other entries. This problem has a linear fractional objective function, for which, Charnes-Cooper transformation can be used to reformulate it into the following linear programming optimization problem \( \square \):

\[
\max_{h^{nt}_{bq} \in \mathcal{H}^{nt}_{bq}} \left( \epsilon^{nt}_{bq} \right)^{\text{T}} h^{nt}_{bq}, \tag{36a}
\]

\[
\begin{aligned}
&\text{s.t.} & \left( \epsilon^{nt}_{bq} \right)^{\text{T}} h^{nt}_{bq} + \mu \sigma^n \right)^{2} &\leq 1, \tag{36b}
& & h^{nt}_{bq} &\leq h^{nt}_{bq} + \mu \varepsilon h^{nt}_{bq}, &\forall b, q, u, n \tag{36c}
& & h^{nt}_{bq} - \mu \varepsilon h^{nt}_{bq} &\leq h^{nt}_{bq}, &\forall b, q, u, n \tag{36d}
\end{aligned}
\]

where \( h^{nt}_{bq} = h^{nt}_{bq}/\mu, \mu > 0 \) and \( \mu > 0 \). Problem \( \square \) can now be efficiently solved using interior-point based methods. Some off-the-shelf convex optimization toolboxes, e.g., CVX.

### 4.2.2 Content Placement

A linear programming (LP) with respect to \( \zeta \) for the content placement problem can be obtained. This problem can be easily solved by existing LP available standard optimization softwares such as CVX with the internal solver MOSEK \( \square \).

### 4.2.3 Backhaul Power and Subcarrier Allocation

The optimization problem is still a mixed-integer nonconvex programming with respect to \( \zeta \) and \( \tilde{p} \) which is difficult to tackle. To make this problem tractable, we first relax each \( \zeta \) to a continuous interval, i.e., \( \zeta \in [0,1] \). Further, new variables \( \mathbf{x} = \mathbf{\zeta \tilde{p}} \) is defined in order to \( \tilde{p} \). Then, we can transform the nonconvex optimization problem into the convex one. This problem can be easily solved by available standard optimization softwares such as CVX with the internal solver MOSEK \( \square \). Note that this relaxation is called time sharing which shows the time percentage that each subcarrier should be used \( \square \).

### 4.2.4 Access Power and Codebook Allocation

The optimization problem is still non-convex with respect to \( \mathbf{p} \) and \( \mathbf{s} \). The difficulty of solution comes from the non-convexity of both objective function and secrecy rate constraint. There is no standard approach to solve such non-convex problem. Therefore, we exploit DC and fractional...
programming in the next sections to transform it into a tractable problem. In the following, we develop a solution for power allocation optimization problem and we remark that this solution can be developed for code assignment in the same way.

4.3 Difference-of-Two-Concave-Functions (D.C.) Approximation

Due to the non-convexity of (26), the optimization problem (26) is still difficult to solve. The standard D.C. optimization problem can be written as \( \min_x \{ F_1(x) - F_2(x) \} \) where \( F_1 \) and \( F_2 \) are two convex components with convex feasible domain. This problem can be solved iteratively by solving a sequential convex program as follows:

\[
\min_x \{ F_1(x) - F_2(x) \} \leq (\nabla F_2(x_0), x - x_0),
\]

at each iteration, where \( x_0 \) is the optimal solution of the \( \varphi \)th iteration used for the \( (\varphi + 1) \)th iteration and \( \nabla F_2(x) \) is the gradient of \( F_2(x) \) evaluated at \( x_0 \). By the sequential convex approximation, DC subproblems are equivalently reformulated as:

\[
\max_{p, \varphi, \delta} \Theta(p, \varphi, \delta),
\]

s.t. \( -R_{buq2}^{E,mt} - R_{buq1}^{E,mt} = 0 \), \( \varphi_{buq}^{mt}, \forall m \in M, t \in F, b \in B, u \in U_b, q \in Q, \)

\[
(38a)
\]

\[
(38b)
\]

where

\[
R_{buq1}^{E,mt} = \log_2 \left( \sum_{b \in B} \sum_{u \in U_b} \sum_{n \in N} \left( \eta_{nm} s_{bu}^m p_{bu}^{mt} h_{bq}^m + (\sigma_q^m)^2 \right) \right)
\]

\[
R_{buq2}^{E,mt} = \log_2 \left( \sum_{b \in B \setminus \{k\}} \sum_{u \in U_b} \sum_{n \in N} \left( \eta_{nm} s_{bu}^m p_{bu}^{mt} h_{bq}^m + (\sigma_q^m)^2 \right) \right)
\]

We first express \( R_{buq}^{E,mt} \) in a D.C. form as:

\[
R_{buq}^{E,mt} = -(R_{buq2}^{E,mt} - R_{buq1}^{E,mt}).
\]

Based on (41), the gradient \( \nabla R_{buq1}^{E,mt} \) with respect to \( p \) is given by

\[
\nabla R_{buq1}^{E,mt} = \frac{\partial R_{buq1}^{E,mt}}{\partial p_{bu}^{mt}} = \frac{\partial R_{buq1}^{E,mt}}{\partial p_{bu}^{mt} x_0}
\]

\[
\ln 2 \sum_{b \in B} \sum_{u \in U_b} \sum_{n \in N} \left( \eta_{nm} s_{bu}^m p_{bu}^{mt} h_{bq}^m + (\sigma_q^m)^2 \right)
\]

\[
\ln 2 \sum_{b \in B} \sum_{u \in U_b} \sum_{n \in N} \left( \eta_{nm} s_{bu}^m p_{bu}^{mt} h_{bq}^m + (\sigma_q^m)^2 \right)
\]

\[
\Theta(p, \varphi, \delta),
\]

\[
(42)
\]

\[
\Theta(p, \varphi, \delta) = \Xi_{\text{Num}}(p, s, \varphi, \delta) \leq \Xi_{\text{Den}}(p, s, \varphi, \delta).
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
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\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
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\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
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\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
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\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
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\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]

\[
\Xi_{\text{Num}}(p, s, \varphi, \delta) - \Xi_{\text{Den}}(p, s, \varphi, \delta)
\]
By the Dinkelbach’s method [23] with a initial value $\chi_0^p$ of $\chi^p$, [45] can be solved iteratively by solving the following problem:

$$\max_{p, \varphi, \delta} \Xi_{\text{Num}}(p, s, \varphi, \delta) - \chi_0^p \Xi_{\text{Dem}}(p, s, \varphi, \delta),$$  \quad (46)

with a given $\chi_0^p$ at the $\varphi$th iteration, where $\varphi$ is the iteration index. $\chi^p$ can be explained as the secure EE obtained at the previous iteration. In $\chi$, the maximization problem is equivalent to

$$\min_{p, \varphi, \delta} \chi_0^p \Xi_{\text{Dem}}(p, s, \varphi, \delta) - \Xi_{\text{Num}}(p, s, \varphi, \delta).$$  \quad (47)

Let $p(\chi_0^p), \varphi(\chi_0^p)$ and $\delta(\chi_0^p)$ denote the solution of $\chi_0^p$ for a given $\chi_0^p$. After each iteration, $\chi_0^p$ should be updated by

$$\chi_0^{p+1} = \frac{\Xi_{\text{Dem}}(p(\chi_0^p), \varphi(\chi_0^p), \delta(\chi_0^p), s)}{\Xi_{\text{Num}}(p(\chi_0^p), \varphi(\chi_0^p), \delta(\chi_0^p), s)}. \quad (48)$$

The iteration process will be stopped when $\Xi$ is satisfied. In practice, we define the terminated condition of the iterative process as:

$$\chi_0 \Xi_{\text{Dem}}(p(\chi_0^p), \varphi(\chi_0^p), \delta(\chi_0^p), s) - \Xi_{\text{Num}}(p(\chi_0^p), \varphi(\chi_0^p), \delta(\chi_0^p), s) \leq \epsilon_3,$$

with a small convergence tolerance $\epsilon_3 > 0$. The algorithm of fractional programming is clarified in Algorithm 2, where $\Psi_2$ is the maximum allowed number of iterations considering the computational time. We use the fractional programming Dinkelbach’s algorithm for the convexified problem [43].

**Theorem 4.** If problems (30) are solvable, the sequence $\{\chi_0\}$ obtained by Algorithm 1 has the following properties: 1) $\chi_0^{p+1} \geq \chi_0^p$; 2) $\lim_{\varphi \to \infty} \chi_0^p = (\chi^p)^\ast$.

**Proof.** Please refer to [45].

Based on the fractional programming, subproblems (50) are associated with a parametric program problem stated as follows:

$$\max_{p, \varphi, \delta} \chi_0 \sum_{t \in T, b \in B} \sum_{m \in M \cap t} \sum_{u \in U_b} s_{m, t}^{u} p_{m, t} - R_{bu}^{E, m, t} - R_{bu}^{D, m, t},$$

$$\sum_{m \in M \cap t} \sum_{b \in B} \sum_{u \in U_b} \left\{s_{m, t}^{u} + R_{bu}^{D, m, t}\right\},$$

s.t. $- (R_{bu}^{E, m, t} - R_{bu}^{D, m, t} - \nabla R_{bu}^{E, m, t} p_{m, t} - p_{m, t}(\varphi)) \leq \varphi_{bu}^{m, t},$

$$\forall m \in M, t \in T, b \in B, u \in U_b, q \in Q,$$

(11) (15) (16) (16d) (26d) (26e).

We propose an iterative algorithm (known as the Dinkelbach method [45]) for solving (50) with an equivalent objective function. The proposed algorithm to obtain power allocation policy $p$ is summarized in Table 2. The convergence to the appropriate energy efficiency is guaranteed. Note that similar algorithm can be used to obtain code allocation policy $s$.

To solve the primary optimization problem, the main optimization problem is decomposed into several subproblems, with each subproblem being in a hierarchical order of the main problem. Depending on different methods to solve each subproblem, the computational complexity of the proposed algorithm is analyzed in Section 5.

### 6 Simulation Results

For simulations, we consider a multi-cell downlink SCMA system where $U$ users are randomly distributed in an area of circle with the radius of 1 km for each BS as the center. The number of users in circle area of $b$th BS is set to $U_b = 4, \forall b$, and the total number of subcarriers and codebooks are set to 8 and 28, respectively. The bandwidth of each subcarrier is 180 kHz [50]. The channels between
the MBS and its users and SBS and its users are generated with a normalized Rayleigh fading component and a distance-dependent path loss in urban and suburban areas, modeled as $PL(dB) = 128.1 + 37.6 \log_{10}(d) + X$ and $PL(dB) = 38 + 30 \log_{10}(d) + X$, respectively [50], where $d$ is the distance from user to BS in kilometers and $X$ is 8 dB log-normal shadowing. We set the frame duration to $T = 0.01$ s [51], [52]. The noise power, $(\sigma_u^2)^2 = (\sigma_b^2)^2 = \sigma^2$, $\forall u, b, n$ is set to $-125$ dBm. We set $D = 2$ and $\eta_{nm} = 0.5$, $\forall n, m$ for SCMA [53]. We set the amount of harvested energy per arrival to $\rho_b = \rho = 0.8, \forall b, \Gamma_b = \Gamma = 0.1$, $\forall b$ and users request contents by normal random generator. In the most popular caching case, the most popular contents is cached at each BS until its storage is full. In this case, the content popularity is modeled as the Zipf distribution with Zipf parameter equals to 0.8. Simulation results are obtained by averaging over 1000 simulation runs.

6.1 Effect of Maximum Allowable Backhaul Transmission Power

In this part, we obtain the backhaul rate for different values of backhaul transmission power with different values of $\alpha$. The simulation results are compared for different caching scenarios such as no caching, random caching, most popular caching and the proposed caching methods. In no caching case, no contents are stored by any BS. Hence, all the requested contents are served by the core network over the backhaul links [54], [55]. In the random caching strategy, the contents are randomly cached by BSs until storage of BSs is full. Content popularity does not matter in this strategy. In the most popular caching strategy, each BS caches the most popular contents until its storage is full [54], [55]. The results are reported in Fig. 3(a). As can be seen, for a fixed transmit power, when $\alpha$ is increased, the resulting backhaul rate increases. As can be seen from this figure, utilizing the caching strategies can reduce backhaul traffic compared to the no caching scheme. Our proposed caching strategy has nearly 43%, 23.4% and 18.5% performance gain in terms of backhaul rate reduction compared to the no caching scheme for different values of $\alpha = 1$, 2, and 3, respectively. It is also notable that the most popular caching strategy causes more reduction in the backhaul traffic, compared to the random caching scheme. However, when all the caching placement are done jointly with the allocation of other network resources, the network performance improves dramatically. This improvement is due to the fact that content placement is done according to network conditions and resources.

Besides, as shown in Fig. 3(a), our caching scheme reduces the total backhaul rate close to almost 11% compared to the most popular caching strategy.

![Image](image_url)

**TABLE 2**

| Fractional Programming Algorithm |
|----------------------------------|
| **Step1:** Initialize the maximum number of iterations $\Psi_3$ and the maximum tolerance $\epsilon_3$; |
| **Step2:** Choose an initial value $x_0^p$ and set iteration index $p = 0$; |
| **Repeat** |
| **Step3:** Solve problem [52] for a given $x_0^p$ and obtain power allocation policy $p(x_0^p)$ (Convex programming); |
| **Step4:** Update $x_0^p$ by [42] to obtain $x_{p+1}^p$; |
| **Step5:** $p = 0 + 1$; |
| **Step6:** If $|x_0^p - x_{p-1}^p| < \epsilon_3$ or $p > \Psi_3$ goto Step7; else goto Step3; |
| **Step7:** Return $p^* = p(x_{p-1}^p), (x^p)^* = x_{p+1}^p$. |
| **End** |

![Image](image_url)

Fig. 3. (a) Backhaul rate, $R_b$, vs. the maximum backhaul transmit power constraint, $P_{\text{Total}}$, for the SFCD scenario. System parameters are: $B = 2, M = 28, F = 2, U = 4, N = 8, Q = 1, K = 6, D = 2, T = 0.01$ s, $\forall k, V_b = 10$ Mbits, $\forall b, E_b^\text{max} = 2$ Joule, $\forall b, \rho = 0.5$ Joule, $\epsilon_b = 0.5$. (b) Energy efficiency, $EE$, vs. the harvested energy per arrival, $\rho$ for the SFCD scenario. System parameters are: $B = 2, M = 28, F = 2, U = 2, N = 8, Q = 2, K = 6, D = 2, T = 0.01$ s, $\alpha_k = 1$ Mbit, $V_b = 10$ Mbits, $\forall b, P_{\text{Total}} = 0.1$ Watts, $E_b^\text{max} = 2$ Joule, $\epsilon_b = 0.5$. 

6.2 Effect of Energy Harvesting

Fig. 3(b) shows the EE as a function of harvested energy per arrival for the SFCD scenario. We compare different EH strategy in terms of EE. In general, by increasing the EH value, the EE is also increased. For larger number of users, the EE is increased. In other words, for the small number of users, there is sufficient power resources, therefore by increasing users, the EE is also increased as shown in Fig. 3(b). However, for too more users, the power resource will be exhausted and thus some users cannot access to network. Even so, due to multiuser diversity, the EE will still increase. For limited battery, due to overflow conditions, the stored energy must be used such that there is enough capacity in the battery for newly arrived energy. In this regard, increasing the value of $\rho$ will increase the energy efficiency at first, but with further increasing $\rho$, the energy efficiency decreases. This is because, from the energy efficiency point of view, the energy consumption would be limited to the amount which maximizes the bit-per-joule quantity. However, for unlimited battery, with increasing $\rho$, the energy efficiency increases at first, and by further increasing $\rho$, the energy efficiency becomes constant since no more energy would be consumed as all the arriving energy could be stored in the battery.

6.3 Effect of File Spliting

Fig. 4(a) shows EE as a function of the harvested energy per arrival, $\rho$, for the SFCD and MFCD scenarios. As can be seen from Fig. 4(a), the MFCD scheme outperforms the SFCD scenario. In the EE communication networks, due to random energy arrivals, there may be not enough energy to transmit a file that has big size in the SFCD scheme. In contrast, in the MFCD schemes, file is split into the several small size files which can be transmitted in the suitable frames to increase EE. In the uniform file splitting, the file is uniformly split into several smaller files with the same size. This scheme has better performance than the SFCD scheme. However, we can improve the network performance by using our proposed method. In the our proposed MFCD scheme, the best size of each split file is obtained to enhance the network performance. This figure also shows that by reducing the size of file, the distance between the graphs for the three scenarios decreases. As seen, the MFCD-proposed file splitting and MFCD-uniform file splitting have closed to almost 9.4% and 6% performance gain in terms of EE compared to SFCD scheme, respectively.

6.4 Transmission Inutility

In this section, we investigate the transmission inutility for the SFCD and MFCD schemes. The transmission inutility is defined by multiplying the outage probability in the transmission delay. The outage probability is defined as probability that there is not enough battery to send content files and the transmission delay is defined as number of frames to send files. Fig. 4(b) demonstrates the transmission inutilities of our proposed schemes for different content file size. As can be seen, by increasing the size of file, the transmission inutility is increased for both schemes. This is due to the fact that there may be not enough harvested energy to send file, and the energy deficiency probability can be increased. Therefore, the outage probability approaches to one in sufficiently big size of files. This deterioration in the MFCD schemes are less than the SFCD scheme. Because in the MFCD schemes, the deficiency probability of energy can be reduced by dividing the content file into several parts and sending each part in different frames. In the proposed splitting scheme, we find the best fractional of content file for each frame which reduces the outage probability more than before. As shown in Fig. 4(b), for larger content file sizes, the MFCD scheme has a higher efficiency in reducing the outage probability. As can be seen, for the size of content files less than 3 Mbits, the SFCD scheme is better, while for the size of large files, the MFCD scheme is better.

6.5 Effect of Channel Uncertainty

Fig. 5(a) shows the access secrecy rate versus channel uncertainty for the SFCD scenario. We see that at bigger channel uncertainty, the secrecy access rate clearly has low value. This is due to the fact that when the uncertainty...
increases, for the worst case scenario, we must guarantee the security for the worst (biggest) channel value of eavesdroppers which leads to low values of secrecy rate. As can be seen, as the number of eavesdroppers increases, the secrecy access rate decreases due to the multiuser diversity gain for eavesdroppers.

Fig. 5. (a) Access secrecy rate, $R^\alpha$, vs. the channel uncertainty, $\varepsilon_h$, for the SFCD scenario. System parameters are: $B = 2, M = 28, F = 2, U = 2, N = 8, Q = 1, K = 6, D = 2, T = 0.01$, $\alpha_k = 1$ Mbits, $\forall k$, $V_b = 10$ Mbits, $P_{Total} = 0.1$ Watts, $E_b^{max} = 2$ Joule, $\forall b, \rho = 0.5$ Joule. (b) Secrecy access and backhaul rates, $R^\beta$ and $\tilde{R}$, vs. the backhaul transmission power, $P_{Total}$, for the SFCD scenario. System parameters are: $B = 2, M = 28, F = 2, U = 4, N = 8, Q = 1, K = 6, D = 2, T = 0.01$, $\alpha_k = 1$ Mbits, $\forall k$, $V_b = 10$ Mbits, $\forall b, E_b^{max} = 5$ Joule, $\forall b, \rho = 0.5$ Joule, $\varepsilon_h = 0.5$.

6.6 Comparison Between Joint backhaul and access optimization and Disjoint Optimization Problem Solution

Fig. 6(a) shows the variation of the EE with the number of frames, $F$ for the SFCD scenario. It is seen that by increasing super frame size, the value of EE increases. In other words, by increasing super frame size, the transmitter can transmit data stream over different frames, then the secrecy access rate and EE will increase. For limited battery storage, with increasing super frame size, at first the EE increases. However, with further increasing super frame size, due to energy overflow constraints, $\rho$, which enforce the transmitters to spend energy, the energy efficiency decreases. Note that, as the value of $\rho$ becomes larger, this decrease in EE happens in lower super frame sizes. For unlimited battery storage, since the overflow constraints, $\rho$, are absent, all the harvested energy is stored in the battery. In this case, increasing super frame size will increase the diversity gain, and hence, the energy efficiency increases.

6.7 Effect of super frame size

In this part, we investigate the performance of the proposed resource allocation algorithm. In Fig. 6(b), we show EE after each iteration at the proposed alternate optimization algorithm. As can be seen, the convergence of the proposed algorithm can averagely be achieved within 700 iterations.

6.8 The Convergence of the Proposed Algorithm

In this paper, we provided a unified framework for radio resources allocation and content placement considering the physical layer security and the channel uncertainty to provide higher energy efficiency. To do so, we considered downlink SCMA scenarios, and we aimed at maximizing the worst case energy efficiency subject to system constraints which determines the radio resources allocation and content placement parameter. Moreover, we proposed two novel content delivery scenarios: 1) single frame content delivery and 2) multi-frame content delivery.
delivery, and 2) multiple frames content delivery. In the first scenario, the requested content by each user is served over one frame. However, in the second scenario, the requested content by each user can be delivered over several frames. Since the optimization problems are nonconvex and NP-hard, we provided an iterative method converging to a local solution. Finally, we showed the resulting secrecy access rate, backhaul rate, and energy efficiency for different values of maximum backhaul transmit power as well as different number of users and various content size. In addition, we compared the performance of the proposed caching scheme with the existing traditional caching schemes. Based on simulation results, via our proposed caching scheme, the performance is approximately improved by 14% and 21% compared to the most popular and random caching schemes, respectively. Moreover, it can be seen that the MFCD scheme can approximately enhance the system performance by 5.2% and 11.1% for small and large files, respectively.

APPENDIX A

PROOF OF LEMMA 1

We jointly find the optimization variables $p, \bar{p}, s, \theta$, and $\zeta$ such that the EE of the proposed system is maximized. Hence, (22) is MINLP and non-convex. We assume that the optimization variables $p, \theta$, and $\zeta$ are constant. In access link, we also assume that one subcarrier is exclusively assigned to at most $D$ users within the cell. We consider the downlink of an SCMA-based access link consisting of $N$ subcarriers, $U$ users and $D = 2$. By assuming that the special $u^{th}$ user’s channel gain on all subcarriers is the largest among all users, the optimal power assigned to user $u$ is equal to $p_{bu}^{mt}/N$, where $p_{bu}^{mt}$ is the transmit power assigned to user $u$ at BS $b$ at frame $t$ on codebook $m$. Then, the challenge is how to allocate the remaining power resource $E_b^t / T - p_{bu}^{mt}$ to $U - 1$ users over all subcarriers. Thus, no subcarrier can be assigned to more than one user. Therefore, a special case of power and codebook optimization problem with $D > 1$ is equivalent to the NP-hard problem considered in [57], and the result follows. Finally, it can be concluded that the main problem (22) is also NP-hard.

APPENDIX B

PROOF OF THEOREM 1

In accordance to the foregoing discussions, for (28) with a given $e_{h_{g'}} (p_{g^{+1}}, \bar{p}_{g^{+1}}, s_{g^{+1}}, \theta_{g^{+1}}, \zeta_{g^{+1}})$ is its optimal solution, while $(p_{g}, \bar{p}_{g}, s_{g}, \theta_{g}, \zeta_{g}, e_{h_{g}})$ is only its feasible solution. We get that

$$\Xi_{EE}(p_{g^{+1}}, \bar{p}_{g^{+1}}, s_{g^{+1}}, \theta_{g^{+1}}, \zeta_{g^{+1}}, e_{h_{g}}) \leq \Xi_{EE}(p_{g}, \bar{p}_{g}, s_{g}, \theta_{g}, \zeta_{g}, e_{h_{g}}).$$

Likewise, for (29) with a given $p_{g}$, $(p_{g^{+1}}, s_{g^{+1}}, \theta_{g^{+1}}, \zeta_{g^{+1}}, e_{h_{g^{+1}}})$ is its optimal solution, while $(p_{g}, s_{g}, \theta_{g}, \zeta_{g}, e_{h_{g}})$ is only its feasible solution. It follows that

$$\Xi_{EE}(p_{g^{+1}}, s_{g^{+1}}, \theta_{g^{+1}}, \zeta_{g^{+1}}, e_{h_{g^{+1}}}) \leq \Xi_{EE}(p_{g}, s_{g}, \theta_{g}, \zeta_{g}, e_{h_{g}}).$$

For relations (30), (31), and (32), this trend is similar. It is naturally concluded that

$$\Xi_{EE}(p_{g^{+1}}, s_{g^{+1}}, \theta_{g^{+1}}, \zeta_{g^{+1}}, e_{h_{g^{+1}}}) \leq \Xi_{EE}(p_{g}, s_{g}, \theta_{g}, \zeta_{g}, e_{h_{g}}).$$

APPENDIX C

PROOF OF THEOREM 2

Because of the convexity of $R_{buq1}^{E,mt}$, it follows that

$$R_{buq1}^{E,mt}(q + 1) \geq R_{buq1}^{E,mt}(q) - \left(\nabla R_{buq1}^{E,t}(q), p_{bu}^{mt}(q + 1) - p_{bu}^{mt}(q)\right),$$

for $p_{bu}^{mt}(q)$ and $p_{bu}^{mt}(q + 1)$ in the feasible domain. We can deduce that

$$- \left(\nabla R_{buq1}^{E,t}(q), R_{buq1}^{E,mt}(q + 1) - p_{bu}^{mt}(q)\right)$$

$$- (R_{buq2}(q + 1) - R_{buq1}(q)) \leq - (R_{buq2}(q) - R_{buq1}(q)).$$
Combined with (55) and (56), we conclude that
\[-(R_{buq}^{E,mt}(q+1) - R_{buq}^{E,mt}(q+1)) \leq -(R_{buq}^{E,mt}(\theta) - R_{buq}^{E,mt}(\theta)).\]  
Equation (57)

Obviously, the current value \(p_{buq}(q+1)\) is smaller than the previous value \(p_{buq}(q)\) while the current solution \(p_{buq}(q+1)\) is better than the previous solution \(p_{buq}(q)\). As a result, the theorem is proved.

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