Cross-Layer Resource Allocation in NOMA Systems with Dynamic Traffic Arrivals

Huiyi Ding  
Department of Electrical and Electronic Engineering  
The University of Hong Kong  
Pokfulam Road, Hong Kong, China  
E-mail: hyding@eee.hku.hk

Ka-Cheong Leung*  
School of Computer Science and Technology  
Harbin Institute of Technology, Shenzhen  
Shenzhen 518055, China  
E-mail: kcleung@ieee.org

Abstract—Non-orthogonal multiple access (NOMA) has become a potential candidate to satisfy the heterogeneous demands in the fifth generation of wireless communication systems. With the optimization on the resource allocation, NOMA can further enhance the system performance. This paper proposes a cross-layer resource allocation framework for downlink NOMA systems. The problem is formulated as a stochastic problem to minimize the long-term total power consumption with dynamic traffic arrivals and time-varying channel under limited feedback. Then, this problem can be transformed to a rate control problem and a mixed-integer programming resource allocation problem solved at each time slot based on the Lyapunov optimization. To reduce the computational complexity, we devise an efficient sub-optimal resource allocation algorithm with the dynamic penalty factor. The simulation results show that our proposed algorithms can reduce the power consumption compared with the two baseline algorithms while satisfying the QoS requirements.

Index Terms—Cross-layer Control, Dynamic Traffic Arrivals, NOMA, Resource Allocation

I. INTRODUCTION

Due to the rapid development of mobile Internet and Internet of Things, many applications with variant demands are expected to be satisfied for the fifth-generation (5G) wireless communication systems. Recently, non-orthogonal multiple access (NOMA) has attracted considerable attention to enhance the system capacity and spectral efficiency. In this paper, we focus on the power domain NOMA (PD-NOMA), which is commonly used to serve multiple users at the same time and frequency domain with different power levels. Typically, for a PD-NOMA system, superposition coding (SC) is adopted at the transmitters to transmit information of multiple users simultaneously, while successive interference cancellation (SIC) is enabled at the receivers to suppress the inter-user interference.

There are many studies in PD-NOMA focusing on the analysis and optimization of the system performance. The performance for a downlink two-point NOMA system was investigated in [1], which has shown the performance improvement of NOMA system compared with the conventional orthogonal multiple access (OMA) techniques. It only adopts the fixed power allocation scheme, where the performance of NOMA systems can be sub-optimal with the inappropriate power allocation factors. To further enhance the system performance, several resource allocation algorithms have been proposed, such as [2] and [3]. The proposed algorithms can substantially improve the performance in both throughput and user fairness. However, these studies mainly ignore the stochastic and time-varying features of traffic arrivals and channel conditions, which may result in unsuccessful transmissions in the packet level.

Some existing approaches partially consider the resource allocation schemes with dynamic traffic arrivals, such as [4], [5], [6], and [7]. A power allocation algorithm is devised in [4] to maximize the long-term time-averaged sum rate, assuming that all the users are multiplexed at the same time, which is impractical for the system with massive number of users in reality. A sub-optimal joint user scheduling and power allocation algorithm (JUSPA) was proposed in work [7] for energy efficiency. However, such heuristic user scheduling scheme assumes full buffer packet backlog, resulting in the degradation of system performance with underutilized resources. The authors in [6] proposed a JUSPA based on both channel conditions and packet-level arrivals with full channel state information (CSI). One common issue for the previous studies is that they assume that the base station (BS) can obtain the perfect CSI, which is impractical for the time-varying channel conditions and the large connectively in realistic environment. Not only full CSI causes large overhead, but also the channel estimation errors may result in the imperfect CSI. To address this issue, limited CSI should be considered. Specifically, 1-bit feedback [8] effectively shows the channel condition with small overhead by comparing the channel condition with a predefined target threshold and responding only one bit signal. Similar to [5] and [8], 1-bit feedback is used in our work to obtain a better CSI than the distribution information of channel conditions with a small overhead. However, the simple 2-user paired NOMA system were considered in the most existing works, such as [3] and [5], limiting the potential of NOMA for spectral efficiency. In general, more users can be multiplexed for higher throughput and spectral efficiency. Besides, the proposed algorithm in [5] employs the exhaustive search to find the optimal JUSPA, which will yield a high computational complexity for large systems in reality. Another issue is that the existing studies have not considered the delay.
constraints. In [5], no packet will be transmitted if the queue length is large, causing the large delay and thereby congestion. Actually, delay performance is an indispensable quality-of-service (QoS) requirement in resource allocation. To overcome the queue congestion and satisfy the delay requirement, traffic rate control should also be considered for each user.

To deal with the above issues, we design a NOMA system with dynamic traffic arrivals and time-varying channel under limited feedback. We devise an optimal cross-layer resource allocation (OA) algorithm, which can jointly control the traffic rate, coordinate user scheduling and allocate transmission power dynamically. The algorithm can reduce the long-term power consumption and satisfy the QoS requirements including the system throughput and delay bound. Based on the Lyapunov optimization and the properties on the logarithm inequalities, the power consumption optimization problem is transformed into a traffic rate control problem and a mixed-integer programming (MIP) resource allocation problem solved at each time slot. However, the optimal problem is NP-hard and there is no computational complexity guarantee for solving the problem using MIP solvers. To reduce the computational complexity and solve the problem online, we devise an efficient sub-optimal resource allocation (SOA) algorithm using difference-of-convex-function (DC) programming and successive convex approximation (SCA) with the dynamic penalty factor, which can solve the problem with polynomial time computational complexity.

The paper is organized as follows. In Section II, we describe the model of the downlink NOMA system and formulate the optimization problem. The proposed algorithms are discussed in Section III. Performance evaluation is given in Section IV. Finally, Section V gives the conclusion.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

We consider a downlink NOMA system in this work, as shown in Fig. 1, where one BS serves a set of user equipment (UE) denoted by $\mathcal{M} = \{1, \ldots, i, \ldots, M\}$ in the cell. The system is assumed to operate in a slotted time mode with unit time slot $t \in \mathcal{T} = \{0, 1, 2, \ldots\}$, where the time interval $[t, t+1)$ is referred to the time slot $t$. The channel between BS and user $i$ suffers from Rayleigh fading and path loss with time-varying CSI. $M$ buffering queues are maintained at BS to store the packets to be transmitted of each user. At the beginning of each time slot, random data packets arrive at the BS, and BS decides whether to admit it into the system or not. Moreover, BS is responsible for the user scheduling and power allocation schemes. According to the 1-bit feedback sent from each user, BS transmits a superimposed signal with appropriate resource allocation. At each receiver, SIC is applied to remove the partial inter-user interference. Each user decodes the stronger signals from other users before decoding its own signal, and regards the other signals as the interference. Hence, the system performance can be optimized, and the QoS requirements can be satisfied by the cross-layer resource allocation.

B. Problem Formulation

The channel gain for each user is $g_i(t) = |h_i(t)|^2 l_i(t)$, where the distance and non-singular path loss between BS and user $i$ are denoted as $r_i(t)$ and $l_i(t) = (1 + r_i(t)^3)^{-1}$, while $|h_i(t)|^2$ follows an exponential distribution. We assume that BS only has the limited knowledge of the CSI, including the distance $r_i(t)$ and the 1-bit feedback from each user. Specifically, a binary indicator denoted as $s_i(t)$ is sent from user $i$ in each time slot $t$. In particular, $s_i(t) = 1$ when $|h_i(t)|^2 l_i(t) \geq \theta$, otherwise $s_i(t) = 0$, where $\theta$ is a predefined threshold.

The channel length, delay, and admitted traffic of user $i$ in time slot $t$ are denoted by $Q_i(t)$, $D_i(t)$, and $A_i(t)$, respectively, where $0 \leq A_i(t) \leq A_{max}$ and $A_{max}$ denotes the maximum traffic rate. The transmit power for user $i$ in time slot $t$ is denoted by $P_i(t)$. Besides, a binary user scheduling variable $x_i(t)$ is introduced, where $x_i(t) = 1$ if the packet for user $i$ is transmitted in time slot $t$, otherwise $x_i(t) = 0$. Specifically, OMA is a special case when $\sum_{i=1}^{M} x_i(t) = 1$. Therefore, the queue dynamic for user $i$ is given as $Q_i(t+1) = [Q_i(t) - x_i(t)]^+ + A_i(t)$.

To deal with the dynamic traffic arrivals, we focus on the long-term system performance rather than the instantaneous one. We introduce the time-averaged queue length for user $i$ as $\bar{Q}_i = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} Q_i(t)$. Similarly, the time-averaged transmit power and delay for user $i$ are denoted as $\bar{p}_i = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} P_i(t)x_i(t)$ and $\bar{D}_i = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} D_i(t)$, respectively. Thus, the time-averaged total power consumption is given by $\bar{p}_{tot} = \sum_{i=1}^{M} \bar{p}_i$.

The decoding order is denoted as $\pi$, where $\pi(i)$ is the user index corresponding to the decoding order $i$. The signals of first $\pi(i-1)$ users are detected and removed from the received signal by user $\pi(i)$ before decoding its own signal. The interference from other users is treated as the noise. Thus, the received signal-to-interference-plus-noise ratio (SINR) at user $\pi(j)$ for decoding the signal of user $\pi(i)$ is given as:

$$\Gamma_{\pi(j)}^{\pi(i)} = \frac{|h_{\pi(j)}(t)|^2 \pi_{\pi(j)}(t) P_{\pi(i)}(t) x_{\pi(i)}(t)}{|h_{\pi(j)}(t)|^2 l_{\pi(j)}(t) \sum_{m=i+1}^{M} P_{\pi(m)}(t) x_{\pi(m)}(t) + \delta^2}$$

(1)
where $\delta^2$ denotes the variance of the additive white Gaussian noise.

To deal with the packet-level scheduling, $\psi_{i}(t)$ is introduced as the probability of successful packet transmission, which is the probability that the packet for user $i(t)$ is sent by BS and also decoded successfully at the user $i(t)$ in time slot $t$. Hence, $\psi_{i}(t) = \Pr(\Gamma_{i}(t) \geq \xi_{i}(t))$, where $\xi_{i}(t)$ is the SNR threshold for user $i(t)$.

Given $\psi_{i}(t)$, we have:

$$\psi_{i}(t) = \begin{cases} \min\{\psi_{i}(t), 1\}, & \text{if } s_{i}(t) = 1, x_{i}(t) = 1 \\ \max\{\psi_{i}(t), 0\}, & \text{if } s_{i}(t) = 0, x_{i}(t) = 1 \\ 0, & \text{otherwise} \end{cases}$$

where $\psi_{i}(t) = e^{-\rho_{i}(t)}$, $\psi_{i}(t) = \frac{-\rho_{i}(t)}{1-e^{-\rho_{i}(t)}}$.

and $\rho_{i}(t) = \max_{j=1,\ldots,\pi} \sum_{m=1}^{\pi} P_{i,j}(m) x_{i,j}(t) - \xi_{i}(j)$.

From energy-efficient communication systems perspective, the objective of this work is to minimize the long-term time-averaged total power consumption, while providing the acceptable QoS requirements for each user and maintaining the queue stability. The optimization problem can be formulated as:

$$\min_{x_i(t), P_i(t), \pi} \psi_{tot}$$

s.t.  
C1 : $0 \leq \sum_{i=1}^{M} P_{i}(t)x_{i}(t) \leq P_{max}$
C2 : $\psi_{i}(t) \geq \eta \psi_{i}(t)$, $\forall i \in \mathcal{M}$
C3 : $x_{i}(t) = \{0, 1\}$, $\forall i \in \mathcal{M}$
C4 : $Q_{\pi}(i) < \infty$, $\forall i \in \mathcal{M}$
C5 : $D_{\pi}(i) \leq \tau_{\pi}(i)$, $\forall i \in \mathcal{M}$

where $\eta$ and $\tau$ denote the threshold of success transmission probability and the delay bound, respectively. In (3), C1 limits the peak transmit power in each time slot. C2 maintains the success probability for transmitted users. C3 is the binary constraint for the user scheduling variables. C4 is the queue stability constraint. The delay bound for each user is shown in C5.

III. CROSS-LAYER RESOURCE ALLOCATION SCHEME

Problem (3) is difficult to solve directly because it is a stochastic problem with binary variables. Hence, we first transform it into a deterministic problem which can be solved in each time slot. The transformed problem can be decomposed into a rate control sub-problem and an MIP resource allocation sub-problem, and solved by an optimal cross-layer resource allocation algorithm. The resource allocation sub-problem is NP-hard, and can be solved optimally using the well-known branch-and-bound (BnB) method or solved approximated using the outer-approximation methods. Many commercial solvers can approximate and solve this problem directly [9]. However, the computational complexity for optimal result grows exponentially. In the worst case, all binary variables have to be enumerated. MIP solvers are usually faster than the enumeration but there is no guarantee for the computational complexity. To improve the computational efficiency and solve the problem with polynomial time complexity, a sub-optimal algorithm is proposed based on the DC penalty function and SCA with the dynamic penalty factor.

A. Problem Transformation

The Lyapunov optimization framework [10] is adopted to transform the stochastic problem into deterministic ones without any statistical information of channel state and user arrival rate. To deal with the delay constraints, we introduce $D_{i}(t+1) = [D_{i}(t) - \tau_{i}A_{i}(t)]^{+} + Q_{i}(t)$ as a virtual delay queue for user $i$. We define the Lyapunov matrix as $G(t) = [Q(t), D(t)]$. Hence, the Lyapunov function becomes $L(G(t)) = \frac{1}{2} \sum_{i=1}^{M} (Q_{i}(t) + D_{i}(t))^{2}$, and the Lyapunov drift becomes $\Delta(G(t)) = \mathbb{E}\{L(G(t+1)) - L[G(t)]\}$.

To minimize the time-averaged total power consumption under the queue stability constraints, we focus on the drift plus penalty (DPP) function in time slot $t$ as:

$$DPP(G(t)) = \Delta(G(t)) + V \mathbb{E}\{\sum_{i=1}^{M} P_{i}(t) x_{i}(t) | G(t)\}$$

$$\leq C + \sum_{i=1}^{M} Q_{i}(t) \mathbb{E}\{A_{i}(t) - x_{i}(t) | G(t)\}$$

$$+ \sum_{i=1}^{M} D_{i}(t) \mathbb{E}\{Q_{i}(t) - \tau_{i}(t) A_{i}(t) | G(t)\}$$

$$+ V \mathbb{E}\{\sum_{i=1}^{M} P_{i}(t) x_{i}(t) | G(t)\}$$

(4)

where $V$ is an arbitrarily positive control parameter which represents the tradeoff between the penalty of power consumption and queue stability, and $C$ is a finite constant which satisfies $C \geq \frac{1}{\tau_{i}} \sum_{i=1}^{M} [(A_{i}(t) - x_{i}(t))^{2} + (Q_{i}(t) - \tau_{i}(t) A_{i}(t))^{2}]$.

B. Traffic Rate Control

In order to minimize (4), the optimal traffic arrival at each time slot is achieved by minimizing the expression as:

$$\min_{A(t)} \psi_{i}(t) A_{i}(t) - \tau_{i}(t) D_{i}(t) A_{i}(t)$$

s.t. $0 \leq A_{i}(t) \leq A_{max}$

and the optimal solution for user $i$ is $A_{i}(t) = A_{i}(t)$ if $Q_{i}(t) \leq \tau_{i}(t) D_{i}(t)$, and $A_{i}(t) = 0$, otherwise.

C. Resource Allocation

1) Optimal Resource Allocation: The deterministic resource allocation problem at each time slot becomes:

$$\min_{x_i(t), P_i(t), \pi} \psi_{i}(t) = \frac{V \sum_{i=1}^{M} P_{i}(t) x_{i}(t) - \sum_{i=1}^{M} Q_{i}(t) x_{i}(t)}$$

s.t.  
C1 : $0 \leq \sum_{i=1}^{M} P_{i}(t) x_{i}(t) \leq P_{max}$
C2 : $\psi_{i}(t) \geq \eta x_{i}(t)$, $\forall i \in \mathcal{M}$
C3 : $x_{i}(t) = \{0, 1\}$, $\forall i \in \mathcal{M}$

(6)

To deal with the probabilistic constraint C2 in (6), we use the properties for logarithm equations and inequalities. Here, we introduce $P_{\pi}(i) = 0$ and $z_{\pi}(i) \leq 0$, where
\[ \hat{P}_{\pi(i)}(t) = P_{\pi(i)}(t)x_{\pi(i)}(t) \] and \[ z_{\pi(i)}(t) = \hat{P}_{\pi(i)}(t) - \xi_{\pi(i)} \sum_{m=1}^{M} \hat{P}_{\pi(m)}(t) \]. Using the auxiliary variables, the total power consumption at each time slot becomes:

\[
\sum_{i=1}^{M} \hat{P}_{\pi(i)}(t) = z_{\pi(j+1)}(t) + \sum_{k=j+2}^{M} \prod_{n=j+1}^{k-1} (1 + \xi_{\pi(n)} \hat{z}_{\pi(n)}(t))
\]

Hence, the total power consumption at time \( t \) can be formulated as:

\[
\sum_{i=1}^{M} P_{\pi(i)}(t)x_{\pi(i)}(t) = \sum_{i=1}^{M} \hat{P}_{\pi(i)}(t) = \sum_{i=1}^{M} \alpha_{\pi(i)}(t) z_{\pi(i)}(t) \tag{8}
\]

where \( \alpha_{\pi(i)}(t) = \prod_{i=1}^{j-1} (1 + \xi_{\pi(j)}), \) for \( i = \{2, \ldots, M\} \), and \( \alpha_{\pi(1)} = 1 \). Then, Constraint C2 in (6) can be transformed as:

\[
C2.1: z_{\pi(i)}(t)/\xi_{\pi(i)} \geq x_{\pi(i)}(t) \max_{j=1, \ldots, M} \{\beta_{\pi(j)}(t)\} \tag{9}
\]

where \( \beta_{\pi(i)}(t) = \frac{\delta^2}{(\alpha_{\pi(i)}(t)(\eta-\alpha_{\pi(i)}(t)))} \) for \( s_{\pi(i)}(t) = 1 \), and \( \beta_{\pi(i)}(t) = \frac{\delta^2}{(\alpha_{\pi(i)}(t)(\eta-\alpha_{\pi(i)}(t)))} \) for \( s_{\pi(i)}(t) = 0 \).

From (9), the problem can be reformulated as:

\[
\min_{x(t), x(t), \pi} V \sum_{i=1}^{M} \alpha_{\pi(i)}(t) z_{\pi(i)}(t) - \sum_{i=1}^{M} Q_{\pi(i)}(t)x_{\pi(i)}(t)
\]

s.t. C1 : \[ 0 \leq \sum_{i=1}^{M} \alpha_{\pi(i)}(t) z_{\pi(i)}(t) \leq P_{\text{max}} \]

C2.1 : \[ \frac{z_{\pi(i)}(t)}{\xi_{\pi(i)}} \geq x_{\pi(i)}(t) \max_{j=1, \ldots, M} \{\beta_{\pi(j)}(t)\} \]

C3 : \[ x_{\pi(i)}(t) = \{0, 1\}, \quad \forall i \in \mathcal{M} \]

Obviously, the optimal decoding order \( \pi^{opt} \) should satisfy \( \beta_{\pi^{opt}(i)}(t) \geq \ldots \geq \beta_{\pi^{opt}(M)}(t) \). Hence, Constraint C2.1 in (11) can be further reformulated as C2.2:

\[
\frac{z_{\pi(i)}(t)}{\xi_{\pi(i)}} \geq x_{\pi(i)}(t) \max_{j=1, \ldots, M} \{\beta_{\pi(j)}(t)\} \tag{10}
\]

Without loss of generality, we use \( i \) to replace \( \pi^{opt}(i) \). Thus, the optimal problem (11) becomes:

\[
\min_{x(t), x(t)} V \sum_{i=1}^{M} \alpha_{i} z_{i}(t) - \sum_{i=1}^{M} Q_{i}(t)x_{i}(t)
\]

s.t. C1 : \[ 0 \leq \sum_{i=1}^{M} \alpha_{i} z_{i}(t) \leq P_{\text{max}} \]

C2.2 : \[ z_{i}(t) \geq \xi_{i} \beta_{i}(t)x_{i}(t), \quad \forall i \in \mathcal{M} \]

C3 : \[ x_{i}(t) = \{0, 1\}, \quad \forall i \in \mathcal{M} \]

Note that Problem (11) is an MIP problem, which is NP-hard. It can be optimally solved by the BnB method and approximately solved by the outer-approximation methods. Most of commercial solvers, such as Cplex, adopt approximation methods with provable upper and lower bounds on the difference between the true value and the approximation, where the \( \epsilon \)-suboptimal point can be found within a finite number of steps. The details for the proposed optimal cross-layer resource allocation (OA) algorithm is shown in Algorithm 1.

### Algorithm 1: OA Algorithm

1. Initialize \( V, \tau, \eta, \) and \( \xi \)
2. For each time slot \( t \) do
   1. Input \( Q(t), D(t) \)
   2. Update admitted traffic \( A^*(t) \) using (5)
   3. Update \( P^*(t) \) and \( x^*(t) \) by solving (12)
3. Output \( \{A^*(t), P^*(t), x^*(t)\} \)

#### 2) Sub-optimal Resource Allocation

However, there is no computational complexity guarantee for solving the problem using MIP solvers. To improve the computational efficiency, we propose an efficient sub-optimal cross-layer resource allocation (SOA) algorithm. It has the polynomial time computational complexity based on DC and SCA with the dynamic penalty factor [11]. The details are shown in Algorithm 2. Note that Constraint C3 in (11) can be rewritten using the DC function as:

\[
C3.1: \quad 0 \leq x_{i}(t) \leq 1, \quad \forall i \in \mathcal{M}
\]

\[
C3.2: \quad \sum_{i=1}^{M} x_{i}(t) - \sum_{i=1}^{M} x_{i}(t)^2 \leq 0
\]

To deal with the non-convex constraint C3.2 in (12), we propose an iterative resource allocation algorithm based on the SCA. We first transform (11) to:

\[
\min_{x(t), s(t)} U_2
\]

s.t. C1, C2.2, C3.1

where \( U_2 = U_1 + \gamma \left( \sum_{i=1}^{M} x_{i}(t) - \sum_{i=1}^{M} x_{i}(t)^2 \right) \) and \( U_1 = V \sum_{i=1}^{M} \alpha_{i} z_{i}(t) - \sum_{i=1}^{M} Q_{i}(t)x_{i}(t) \). Actually, the second term in \( U_2 \) can be regarded as a penalty term with the penalty factor \( \gamma \). It is proved in [12] that (11) and (13) are equivalent when \( \gamma \) is a moderately high value. Existing methods in [3] and [13] used the pre-defined \( \gamma \) to solve the problem. However, the result may be degraded if \( \gamma \) is chosen inappropriately. Actually, a larger value of \( \gamma \) can provide binary or near binary solutions for user scheduling, while a smaller value of \( \gamma \) results in performance degradation with inappropriate user scheduling. However, the bound of penalty factor is computationally intractable. To address this challenge, we propose an iteration algorithm to obtain a suitable penalty factor \( \gamma \). As shown in Steps 8 to 12, \( \gamma \) is initialized as a small value and increased in each iteration with a constant value \( \epsilon \) till the penalty term vanishes.

To deal with the non-convex objective function in (13), we use the first order Taylor series approximation. Hence, the upper bound of the objective function for the given value of \( x_{i}^k(t) \) at the \( k \)-th iteration is given as \( U_2^k = U_1 + \theta^k \left( \sum_{i=1}^{M} x_{i}(t) - \sum_{i=1}^{M} x_{i}^k(t)^2 - 2 \sum_{i=1}^{M} x_{i}^k(t)(x_{i}(t) - x_{i}^k(t)) \right) \). The iterative approach is used to tighten the obtained upper bound. The

Authorized licensed use limited to: The University of Hong Kong Libraries. Downloaded on August 08,2020 at 15:05:28 UTC from IEEE Xplore. Restrictions apply.
problem solved in the $k$-th iteration becomes:

$$\min_{x(t), z(t)} \tilde{U}^k$$

$$\text{s.t.} \quad C1 : \quad 0 \leq \sum_{i=1}^{M} \alpha_i z_i(t) \leq P_{max}$$

$$C2.2 : \quad z_i(t) \geq \xi_i \beta_i(t)x_i(t), \quad \forall i \in \mathcal{M}$$

$$C3.1 : \quad 0 \leq x_i(t) \leq 1, \quad \forall i \in \mathcal{M}$$

(14)

The convergence and the computational complexity of SCA method are proved in [3] and [14]. Suppose the algorithm (14) will converge after $K_0$ iterations as $|\tilde{U}_k^{K_0} - \tilde{U}_k^{K_0-1}| < \varepsilon$ and the solution is $\{x^*(t), z^*(t)\}$. Yet, $x^*(t)$ may be neither zero or one. Hence, we need to project the user scheduling variables $x(t)$ to the binary values by rounding to $[x(t)]_b \in \{0, 1\}^M$, and then solve (13) with given $[x(t)]_b$ to get the final solution for power allocation.

**Algorithm 2 SOA Algorithm**

1. Initialize $V$, $\tau$, $\eta$, $\xi$, $K_{max}$, $\gamma^0$ and $c$
2. for Each time slot $t$ do
3. input $Q(t)$, $D(t)$
4. Update admitted traffic $A^*(t)$ using (5)
5. for $k = 1 : K_{max}$ do
6. Solve (15) with $P^{(k-1)}(t), x^{(k-1)}(t)$ to obtain optimal $P^*(t), x^*(t)$
7. Update $P^{(k)}(t) = P^*(t)$ and $x^{(k)}(t) = x^*(t)$
8. if $||x^* - x^{(k-1)}|| \geq \epsilon_1$ then
9. $\gamma_k = \gamma_{k-1} + c$
10. else
11. $\gamma_k = \gamma_{k-1}$
12. end if
13. if $|\tilde{U}^k_{2} - \tilde{U}^{(k-1)}_{2}| \leq \varepsilon$ then
14. Return to Step.17
15. end if
16. Project $x^*(t)$ to $[x(t)]_b \in \{0, 1\}^M$
17. Solve (14) with given $[x(t)]_b$ to calculate $P^b(t)$
18. Output $\{A^*(t), P^b(t), [x(t)]_b\}$
19. end for

IV. PERFORMANCE EVALUATION

In this section, we evaluate the performance of the NOMA system with our proposed methods using Matlab. We consider a single cell downlink NOMA system with one BS located at the center. The parameters are commonly used in the existing studies, such as [5] and [6]. The cell radius, the channel bandwidth, and the variance of noise are set as 1000 m, 180 kHz, and $-174$ dBm/Hz. We set the path loss coefficient $\beta = 3$. The threshold of success transmission probability and the feedback threshold are set as 0.9, and $\theta = \frac{2\sigma_L^2}{P_{max}}$. We compare our proposed optimal algorithm (OA) and the sub-optimal algorithm (SOA), with the baseline algorithms for resource allocation proposed in [4] and [15], denoted as fast decision criteria (FDC) algorithm and random near user and random far user (RNRF) selection, respectively. FDC assumes that all users are multiplexed together, while RNRF randomly schedules two users at the same time with the fixed power allocation.

Fig. 2 illustrates the time-averaged total power consumption of different algorithms versus the number of users. The Lyapunov control parameter is set as 20. The results indicate that the power consumption increases with the number of users for all algorithms under study. RNRF has the highest power consumption, followed by FDC, SOA, and then OA. It can be observed that our proposed algorithms can effectively reduce the power consumption, especially when the number of users becomes larger. Particularly, the results for OA is similar as SOA, but OA outperforms SOA Algorithm when the number of user becomes large.

In order to further explain the impact of user scheduling on the performance, Fig. 3 shows the distribution for the number of multiplexed users. In both 5-user and 10-user NOMA systems, the multiplexed number of users in FDC and RNRF are set to the total user number and two. As shown the Fig. 3, the number of multiplexed users having the largest probabilities are 4 and 6 in the 5-user and 10-user NOMA systems, respectively. The reason is that the resources are not fully utilized in the 2-user multiplexed system, and the $M$-user multiplexed scheduling scheme in FDC may cause high interference. It can be illustrated that the dynamic user scheduling can save more power with time-varying channel conditions and dynamic traffic arrivals.

Fig. 4 shows the dynamics of the total queue backlog in 5000 time slot using the rate control with SOA when $M = 10$. It can be seen that the queue length is bounded, which means that our algorithm can ensure queue stability and the long-term QoS constraints are satisfied.

We further investigate the impact of the control parameter $V$ for SOA Algorithm. As shown in Fig. 5, it can be observed that the queue backlog increases and the total power consumption decays with $V$. This means that power saving is weighted larger and the weight for minimizing the queue length becomes intolerant when $V$ becomes larger.
For the same value of $V$, more power is consumed for the system with a larger threshold. Actually, the SNR threshold is related to the required throughput for each user according to Shannnon–Hartley Theorem, and the system with a larger threshold causes a larger power consumption.

V. CONCLUSION

In this work, we study the downlink NOMA systems with dynamic traffic arrivals and time-varying channel under limited feedback. The cross-layer resource allocation scheme aims to minimize the long-term time-averaged total power consumption with QoS requirements. One efficient approach is developed to reduce the computational complexity using DC and SCA with the updated penalty factor. Performance evaluation is conducted to demonstrate that the proposed OA and SOA algorithms can significantly reduce the power consumption while satisfying the QoS requirements. In the future, we plan to extend our work to the multi-cell systems with multiple sub-carriers.

REFERENCES


