Social-Aware Energy-Efficient Data Offloading With Strong Stability

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***Abstract*— The exploding popularity of mobile devices enables people to enjoy the benefits brought by various interesting mobile apps. The ever-increasing data traffic has exacerbated energy consumption on both cellular service providers and mobile users. It has become an urgent need to reducing the energy consumption in the cellular network while satisfying users' increasing traffic demands. Mobile data offloading is an effective energy-saving paradigm to tackle the above-mentioned problem. However, the current approaches cannot fully address the issue in terms of user demands and offloaded traffic. With the observation that duplicated data transmission often happens in the crowd with similar social interests, we deploy device-to-device (D2D) data offloading to achieve the energy efficiency at the user side while adapting their increasing traffic demands. Specifically, we investigate the stochastic optimization of the long-term time-averaged expected energy consumption while guaranteeing the strong stability of the network by utilizing the social-aware and energy-efficient D2D mobile offloading. By jointly considering interference among D2D users, social-aware caching, link scheduling, and routing, an offline finite-queue-aware energy minimization problem is formulated, which is a time-coupling stochastic mixed-integer non-linear programming (MINLP) problem. We propose an online finite-queue-aware energy algorithm by employing the Lyapunov drift-plus-penalty theory. Extensive analysis and simulations are conducted to validate the proposed scheme.**

***Index Terms*— D2D communication, data offloading, social-awareness, energy-efficiency, cross-layer optimization, network strong stability.**

I. Introduction

WITH the rapid growth of the popularity of mobile devices and Internet services, people enjoy more benefits than ever before. For example, communicating with friends and watching videos at any time and anywhere become a reality. However, such operations generate a huge amount of data traffic. According to the report from the Cisco, global mobile data traffic will increase sevenfold between 2016 and 2021, reaching 48.3 EB per month by 2021 [1]. On the one hand, the explosively increasing data traffic burdens mobile operators with large operational expenditure [2]. On the other hand, it leads to a significant increase in energy consumption and thus puts an adverse effect to the environment [3]. As shown in [4], the amount of CO_2 emissions from the cellular networks will be 345 million tons by 2020. As a result, it is critical to investigate effective solutions to reduce energy consumption while adapting to the ever-increasing data traffic demands.

Mobile data offloading is a promising paradigm to address the above challenge by utilizing complementary and revolutionary networking approaches (e.g., small cell, WiFi offloading, and opportunistic communication) to deliver mobile data originally planned for cellular networks [2]. Instead of requesting data from base stations, users either access data from other users or offload data to other requested users with the help of the Device-to-Device (D2D) communication. Hence, energy consumption at base stations is largely reduced. Taking a step further, incorporating mobile users' social behaviors into consideration facilities the above idea in real life. Specifically, users with similar social interests often group together in a region, which potentially results in similar content requests. For example, users gathered in specific attractions, such as Disneyland, may request similar contents related to those attractions. Such a characteristic is also reflected in social networks, where socially-related data shared among social ties are similar or even identical (e.g., similar photo updates on Facebook). The above observation leads us to consider whether we can avoid duplicated requests/retrievals in order to reduce the number of accesses to the cellular network. Having the offloaded data, similar social interests among users will motivate them using D2D communication for further data dissemination [5], which would greatly relieve the traffic burden at base stations and thus free energy consumption.

However, energy consumption in D2D communication becomes one of the most critical challenges for the deployment. Frequently transceiving data between battery-powered mobile devices could quickly drain their energy [6], [7]. Meanwhile, arbitrarily caching data in their buffer will bring trouble due to limited buffer size. Even worse, the stability of the entire network suffers from break-off users [8], [9]. In our paper, we leverage users' social preference to reduce energy consumption on mobile devices, and keep the stability of the entire system while satisfying users' traffic demands. Specifically, we mainly focus on the following problems:

- **Whether to cache or offload data?** It relies on the current caching queue size and the underlying wireless environment. When the channel condition is poor,

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transmitting the same amount of data results in higher energy consumption. Rather than forwarding the data to the next hop, the user keeps them in a queue and waits for a better channel condition. However, the cumulative queuing data may surpass the buffer size and further affect network stability. Therefore, each user has to make a decision on whether to forward the data or queue it for energy saving purpose.

- **How much data to be cached or offloaded?** Since the energy and the queue size are limited, each user sets different preferences over caching and offloading data for others, which is addressed by allocating different queue sizes and data transmission rates according to their social interests to offloaded data.
- **Who will cache and offload data?** In a wireless environment, the same data can be cached at different users and one user can cache for multiple data. If more users help cache and offload data, the overall system-wide energy consumption is reduced by decreasing the transmission ranges between users. However, these users inevitably increase energy consumption at their own sides. Hence, users who cache and offload data should be selected.
- **How does social preference work?** Users have different interests in different kinds of data. They could affect the data offloading according to their preferences. For example, when the channel condition is poor, they assign a larger buffer size for the interested data. Thus, the energy consumption is decreased. Based on their preferences, users can flexibly allocate buffer size to data, which will guarantee network stability.

Obviously, energy consumption, channel condition, and network capacity in social-aware data offloading are tightly coupled. To answer those questions, we present a cross-layer optimization framework. An offline energy optimization problem $P1$ is formulated aiming at minimizing the time-averaged value of energy consumption at all users by jointly considering the correlation between random channel conditions, users' social preferences, network capacity and transmission scheduling, which turns out to be a time-coupling stochastic Mixed-Integer Non-Linear Programming (MINLP) problem. Previous approaches applying Dynamic Programming (DP) always suffer from the "curse of dimensionality" problem [10]. Besides, solutions using DP require detailed statistical information on system random variables, which are difficult to obtain in practice. Therefore, based on deploying Lyapunov optimization theory [11], we reformulate an equivalent problem $P2$ and propose an online energy approximation problem $P3$. Different with the offline energy optimization requiring the knowledge of the network statistics, the online energy approximation problem $P3$ does not require any statistic knowledge of the random process. However, $P3$ is still a MINLP which is NP-hard and needs to be solved in each time slot. By introducing a virtual queue, we decompose P3 into three subproblems: link scheduling and power allocation ($S1$), content allocation ($S2$), and routing ($S3$). Three algorithms are developed to solve them based on the current network states only respectively. Finally, we demonstrate the network stability by proving all the queues are finite (Theorem 1). Meanwhile, we prove that the proposed algorithm leads to an upper and lower bound (Theorem 2 and Theorem 3) to the original problem, where $\phi^*_{P3} - \frac{B}{V} \leq \phi^*_{P1} \leq \phi^*_{P3}$. ϕ^*_{P1} and ϕ^*_{P3} are the optimal results of $P1$ and $P3$, respectively. B is a constant and V represents the weight on how much we emphasize on the energy consumption minimization in $P3$. As we can see, $\frac{B}{V}$ goes to 0 as V increases, in which the minimized time-averaged expected energy is obtained in $P1$.

The rest of this paper is organized as follows: Section 2 briefly reviews the existing D2D enabled data offloading schemes and studies the effect brought by social characteristics, together with Lyapunov optimization techniques applied in wireless networks. In Section 3, we introduce our system architecture and network model. The formulation of an offline energy minimization optimization problem is given in Section 4. In Section 5, based on Lyapunov optimization theory, we formulate an online finite-queue-aware energy minimization problem and design a decomposition based approximation algorithm to solve it. We prove that the proposed approximation algorithm guarantees network strong stability, and derive both a lower and upper bound on the optimal result of the offline optimization problem in Section 6, followed by the simulation results. Finally, we conclude our work in Section 7.

II. Related Work

A. D2D Enabled Data Offloading

In D2D enabled data offloading framework, some users are chosen as helpers/relays [12]–[15] to receive the data via cellular networks. Then, those users further propagate the data among all the users through D2D communications. It is further classified into two categories: in-band offloading and out-of-band offloading [16], where the direct communication between users occupies the licensed cellular spectrum and unlicensed spectrum (e.g., WiFi-Direct, Bluetooth) respectively. In-band offloading may improve the resource utilization by reusing the spectrum for the users that are physically in close proximity to communicate with each other at a high rate and low power consumption. The developments in the 3GPP LTE Standard (Rel-12) have proposed integrating direct in-band communication capabilities into the future cellular architecture [17]. Li *et al.* in [18] study the realistic bound of an offloading strategy exploiting LTE-D2D in a large-scale scenario. Their simulation results confirm that augmenting the number of users in the cell largely benefits to offloading, increasing its efficiency. In that case, D2D transmissions account for up to 50% of the traffic, which shows the feasibility of in-band offloading.

Since direct transmissions take place in the same band as the cellular transmissions, in-band offloading provides additional flexibility to the network but raises issues on mutual interference and resource allocation. Thus, previous works mainly focus on interference management and transmission coordination problems. In [19], the radio resource allocation is optimized to help decrease the mutual interference between D2D communications and the primary cellular network. Xu *et al.* propose a reverse iterative combinatorial auction mechanism to allocate spectrum resources between cellular users and D2D pairs [20]. Doppler *et al.* in [21] limit the maximum transmission power of D2D peers to alleviate the interference. With the explosive increase of data traffic, power allocation puts an effect on not only the interference management but also device battery. However, how to improve energy efficiency at mobile users receives little attention in D2D enabled data offloading. Meanwhile, social-characteristics, which play an important role in other offloading schemes [22], [23], are not considered.

B. Social-Enabled Data Offloading

The "like-me" principle [24] describes a well-accepted nature of human interaction that people like to interact with those who are similar to themselves. An experiment analyzing the relationship between the contact rate and the number of identical attributes is conducted in [25], [26] based on the trace file collected during the INFOCOM 2006 [27]. Its result shows that the contact rate in terms of the number of contacts between two users increases with the increment of identical attributes, which further validates the "like-me" principle. In addition to that, Hsu *et al.* in [28] show that users who share similar interests intend to form a group and they forward messages to others in the group more efficiently. From the above phenomena, in the scenario where users with attribute similarities form the attribute-similar group, we infer that the content dissemination is much more efficient when the social characteristics are considered. As in our previous work [29], [30], users are more satisfied with the data offloading process when we take into consideration the social effect brought by users' similar attributes.

The deployment of the above social characteristics has been addressed in data offloading. Li *et al.* in [31] demonstrate that we can leverage the social behaviors to assist D2D communication in order to enhance the achievable system performance. In [22], social participation and interaction are exploited to help select the target users in order to minimize the mobile data traffic over the cellular network. Zhang *et al.* and Wang *et al.* exploit social network characteristics for assisting the ad hoc peer discovery in [32] and [33], respectively. Social characteristics are also applied to resource allocation in D2D communication. In [33], a two-step coalition game is formulated to achieve optimal spectrum allocation by deploying social times in human-formed social networks. Although the social characteristics are utilized to improve the energy efficiency in [34], they do not consider the randomness in D2D communication, e.g., channel condition and cellular users. However, such randomness would result in serious changes in the network. In our paper, we investigate how to minimize the energy consumption at mobile users (D2D users) while satisfying their traffic demands and network stability under the varying channel condition.

C. Lyapunov Optimization Method

Lyapunov optimization theory has been adopted to investigate stochastic optimization problems in communication and queuing systems [8], [9], [11], [35]–[38]. However, the queues

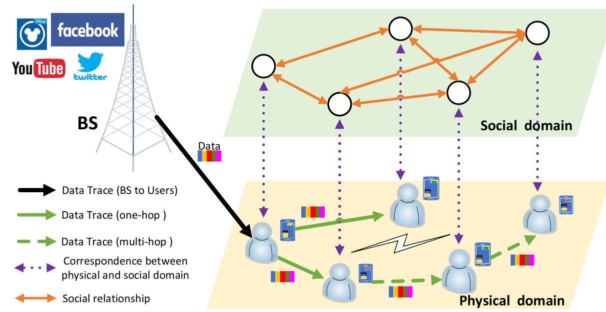

Fig. 1. System model.

are not guaranteed to be finite in [8], [9], [35], which destroys the network stability. Although finite queue sizes are maintained in [35]–[37], some packets are dropped as a cost in opportunistic scheduling scheme. Hence, network utility is lowered. Based on Lyapunov optimization framework, the authors in [9] address social preference of users and apply back-pressure based transmission scheduling to achieve guaranteed utility optimality. Li *et al.* in [39] employ Lyapunov optimization theory to develop online crowdsourcing algorithms. Liao *et al.* in [40] propose an online finite-queue-aware energy cost minimization problem with the help of Lyapunov optimization theory. The above two works guarantee both network stability and utility. However, they do not consider the social characteristics among nodes. Besides, the work [40] deploys a fixed modulation scheme whereas the simulation results in [41] demonstrate the effectiveness on the users' utility using an adaptive modulation scheme. Motivated by the above work, we try to minimize the energy consumption in D2D data offloading by taking social characteristics and adaptive modulation into accounts based on Lyapunov optimization theory in our paper.

III. System Models

A. System Architecture

We take data dissemination in the Disney World as an example, where users with similar social interests group together in the same place, e.g., Rock 'n' Roller Coaster Starring Aerosmith attraction. They request the same contents, e.g., videos related to the attraction, whereas WiFi is not accessible. As shown in Fig.1, instead of getting the requested contents from the base station (BS) directly, D2D offloading is deployed to satisfy users' requests. Specifically, users with the largest cache are chosen as the **representative users** to get the contents from the BS, which are further transmitted among the crowd via D2D communication. To reuse the network resource, all the D2D communications occur on the fixed spectrum bands, which introduces possible interference between different D2D communications and hence would affect the achievable communication rate. In order to prevent interference and improve the energy efficiency at mobile users, the cellular network takes charge of the whole process including network management, link scheduling and resource allocation taking advantage of the social relationships among users.

TABLE I
NOTATION TABLE

$\mathcal{U}$	user set
$\mathcal{L}$	content set
$\mathcal{C}$	modulation order set
$P_{ij}^m(t)$	power of transmission from user i to user j on band m
$P_i^{rev}(t)$	receiving power at user i
$e_i(t)$	total energy consumption at user i
Δt	duration for one time slot
$Q_i^l(t)$	data queue for content l at user i
$Y_{ij}(t)$	virtual link-layer queue from user i to user j
$\rho_i^l(t)$	user i's interest in content l
p_i^l	buffer size for data queue $Q_i^l(t)$
$f_{ij}^l(t)$	amount of content l offloaded from user i to user j
$c_{ij}^l(t)$	content l's maximum transmission rate from user i to user j on band m
c_{ij}^{max}	content l's maximum transmission rate from user i to user j
$s_{ij}^m(t)$	Binary Var: band m is assigned for transmission from user i to user j
$s_{ij}^{mc}(t)$	Binary Var: band m is assigned for transmission from user i to user j with modulation order 2^c
$v_l(t)$	amount of content l, maximum: v^{max}
v^{max}	maximum amount of content received from BS
λ	parameter determined by system controller
V	weight on importance on energy minimization

B. Network Model

As described in Fig. 1, a set of users $\mathcal{U} = \{1, 2, \cdots, U\}$ with the common interests request new contents from the service provider. We represent the above contents using a set $\mathcal{L} = \{1, 2, \cdots, L\}$. Since these users are in close proximity, they get the requested contents either from the BS via cellular communication or from others having common interests via D2D communication. Each content l is further denoted as a tuple $\{f_{ij}^l(t), i, j\}$, indicating the amount of content l offloaded from the caching user i to the requesting user j in time slot t. Because users have different communication interfaces and locate at different positions, they occupy different spectrum bands. Let $\mathcal{M}_i$ denote the set of available spectrum bands the user i has. $\mathcal{M}_i$ might be different from $\mathcal{M}_j$, i.e., $\mathcal{M}_i \neq \mathcal{M}_j$ for $i \neq j$, $i, j \in \mathcal{U}$. All the available spectrum bands compose a spectrum set $\mathcal{M} = \{1, 2, \cdots, M\}$ and $\mathcal{M}_i \subset \mathcal{M}$ for each user i. In addition, we assume the bandwidth of band m is an i.i.d. random process denoted by $\{W^m(t)\}_{t=0}^{\infty}$, which is observed at the beginning of each time slot.

Table I summarizes the main notations for ease of reference, where t denotes in the time slot t.

C. Network Rate Stable and Strongly Stable

We first introduce definitions and theorems of Lyapunov optimization [11]. We denote those theorems as lemmas used for scheme design and analysis later.

Definition 1: The time average of a random process $a(t)$, denoted by $\overline{a}$, is $\overline{a} = \lim_{T\to\infty} \sum_{t=0}^{T} \frac{1}{T}\mathbb{E}[a(t)]$. □

Definition 2: A discrete time process $a(t)$ is rate stable if $\lim_{t\to\infty}\sup\frac{a(t)}{t} = 0$ with probability 1, and strongly stable if $\lim_{T\to\infty}\sup\frac{1}{T}\sum_{t=0}^{T}\mathbb{E}[a(t)] < \infty$. □

Lemma 1 (Queue Rate Stability [11]): Let $Q(t)$ denote the queue length of a single-user discrete time queuing system, whose initial state $Q(0)$ is a non-negative real-valued random variable, and future states are driven by stochastic arrival and transmission processes $a(t)$ and $b(t)$ according to the following dynamic equation:

$$Q(t+1) = \max\{Q(t) - b(t), 0\} + a(t), t \in \{0, 1, 2, \cdots\}$$

Then $Q(t)$ is rate stable if and only if $\overline{a} \leq \overline{b}$. □

Lemma 2 (Necessity for Queue Strong Stability [11]): If a queue $Q(t)$ is strongly stable, and there is a finite constant c such that either $a(t) + b^-(t) \leq c$ with probability 1 for all t, where $b^-(t) \triangleq -\min\{b(t), 0\}$,[1] or $b(t) - a(t) \leq c$ with probability 1 for all t, then $Q(t)$ is rate stable, i.e., $\overline{a} \leq \overline{b}$.

Besides, we say that a network is rate stable or strongly stable if all queues in this network are rate stable or strong stable as described above. □

IV. ENERGY CONSUMPTION OPTIMIZATION

In this section, we investigate the energy consumption optimization problem given cross-layer constraints in D2D data offloading.

A. Energy Consumption

For each offloading user, he consumes the energy when he either transmits the contents or receives the requested contents. Denote the energy consumed at user i as $E_i(t), i \in \mathcal{U}$, in time slot t,

$$E_i(t) = \sum_{j\in\mathcal{U}, j\neq i} \sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} P_{ij}^m(t)s_{ij}^m(t)\Delta t + P_i^{rev}s_{ji}^m(t)\Delta t, \quad (1)$$

where the user i consumes the power $P_{ij}^m(t)$ to transmit the contents to the user j using band m. P_i^{rev}, a constant, denotes the power the user i spends receiving the contents. We suppose Δt to be the time duration in each time slot, and $s_{ij}^m(t)$ is a binary transmission indicator where $s_{ij}^m(t) = 1$ means that user i transmits to user j on band m in time slot t. Otherwise, $s_{ij}^m(t) = 0$.

B. Interference Constraints

To mitigate the interference and improve the throughput when different users offload contents simultaneously, we investigate the constraints from the physical layer.

Based on a widely applied model [42]–[44], the power propagation gain from user i to user j, denoted by g_{ij}, is,

$$g_{ij} = d(i,j)^{-\gamma}, \quad (2)$$

where $d(i,j)$ is the Euclidean distance between user i and j and γ represents the path loss exponent. Here we assume that the coherence bandwidth of each band is larger than the bandwidth itself so that each band is flat. Meanwhile, the coherence time of the channel is larger than the duration of a time slot so that the fading remains constant in each time slot. In addition, users are assumed to be in the same location during content transmission.

[1] Based on [11], the value of $a(t)$ is assumed to be non-negative. For most physical queuing systems, $b(t)$ assumed to be non-negative, although it is sometimes convenient to allow $b(t)$ to take negative values.

Given the propagation gain in (2), according to [42], the signal-to-interference-plus-noise ratio (SINR) of the signal received at j from i on band m becomes,

$$SINR_{ij}^{m}(t) = \frac{g_{ij}P_{ij}^{m}(t)}{\eta_j W^m(t) + \sum_{k\neq i, v\neq j} g_{kj}P_{kv}^{m}(t)}, \quad (3)$$

in which we denote η_j as the thermal noise power density at user j. $W^m(t), m \in \mathcal{M}$ represents the bandwidth of the current spectrum being occupied. We simulate the changes of the current channel condition by changing $W^m(t)$. As in [45], [46], the content transmission is successful only if the received SINR at user j satisfies,

$$SINR_{ij}^{m}(t) \geq \Gamma, \quad (4)$$

where Γ is a threshold that depends on the current modulation scheme and the target bit error rate (BER) P_b [42]. To adapt the current channel condition, we deploy an adaptive M-order quadratic amplitude modulation (M-QAM) scheme, where the modulation order O is chosen from an order set $\mathcal{C} = \{2^1, 2^2, \cdots, 2^C\}$. Hence, we have different possible thresholds as,

$$\Gamma_{\log_2 O} = -\frac{(O-1)\ln(5P_b)}{1.5}, \quad O = 2^1, 2^2, \cdots, 2^C. \quad (5)$$

Suppose that ideal Nyquist data pulse is applied on modulation. The spectrum efficiency of M-QAM is $\log_2 O$ bps/Hz [42]. Let $\Gamma_{C+1} = \infty$. When $\Gamma_{\log_2 O} \leq SINR_{ij}^{m}(t) \leq \Gamma_{\log_2 O+1}$, the achievable data rate from user i to user j on band m is,

$$c_{ij}^{m}(t) = W^m(t)\log_2 O(t). \quad (6)$$

C. Network Layer Constraints

It is an efficient way to improve the energy efficiency by considering the channel condition changes. Instead of offloading the contents to other users when the channel condition is poor, each user would like to keep the contents until that channel condition becomes better. Hence, each user maintains a content queue $Q_i^l(t), i \in \mathcal{U}, l \in \mathcal{L}$ for his received content at the network layer. For every queue Q_i^l at each user, it is updated in the following,

$$Q_i^l(t+1) = \max\left\{Q_i^l(t) - \sum_{j\in\mathcal{U}, j\neq i} f_{ij}^l(t), 0\right\} + \Big(\sum_{\{j|i\neq j\}} f_{ji}^l(t) + v_l(t)\mathbf{1}_{\mathbf{i=s_l}}\Big). \quad (7)$$

If $Q_i^l(t) = 0$, the user i is not on the offloading path for the content l in the current time slot. In (7), the binary variable $\mathbf{1}_{i\in s_l}(i \in \mathcal{U})$ indicates whether the user i is the representative user who receives the content l from the BS. We use $v_l(t)$ to denote its amount in the unit of the number of bits, $v_l(t) \leq v^{max}$, where the constant v^{max} denotes the maximum amount of content received from base station. Note that we suppose the value of $v_l(t)$ is known at the beginning of each time slot. Because there is no incoming data from other users at the source user of session l, we have the following constraint,

$$\sum_{\{j\neq i|i\}} f_{ji}^l(t) = 0, \forall i = s_l, l \in \mathcal{L}. \quad (8)$$

D. Social Preference in Queue

We define a rational number $\rho_i^l \in [0,1]$ to denote user i's social interests on content l. The more interesting to the contents, the larger ρ_i^l is. Our social preference in queue is reflected on the maximum queue size to the contents. To be specific, $p_i^l = F(\rho_i^l), i \in \mathcal{U}$ denotes the maximum queue size user i provides for by-passing content $l \in \mathcal{L}$. $F(\cdot)$ is a positive function that differentiates the queue size allocated to contents with different social preferences ρ_i^l of user i. We suppose $F(\cdot)$ is an increasing function with users' social preference ρ_i^l. It means users would like to provide larger queues for caching their interested contents. Specifically, we denote $p_i^l = (1+\alpha\rho_i^l)p_{s_l}^l$, where $p_{s_l}^l$ is the maximum queue size user s_l provides for content l from base station and α is the weight to strengthen the social preference's effect to the maximum buffer size. The reason for 1 is to ensure that user still participates the data offloading process even he is not interested in the content. Otherwise, in the worst case that no user is interested in the contents, they all keep the contents to themselves and thus data offloading is stopped. In addition, we assume $\alpha = 1$.

E. Link Scheduling Constraints

In this subsection, we illustrate the power allocation and link scheduling on content dissemination. Since each user is unable to transmit to or receive from multiple users on the same band, given the binary transmission indicator $s_{ij}^m(t)$ mentioned above, we have,

$$\sum_{j\in\mathcal{U}, j\neq i} s_{ij}^m(t) \leq 1, \text{and} \sum_{i\in\mathcal{U}, i\neq j} s_{ij}^m(t) \leq 1. \quad (9)$$

Besides, due to "self-interference" at the physical layer, a user cannot use the same frequency band for both transmission and receiving at the same time. Hence,

$$\sum_{i\in\mathcal{U}, i\neq j} s_{ij}^m(t) + \sum_{q\in\mathcal{U}, q\neq j} s_{jq}^m(t) \leq 1. \quad (10)$$

Meanwhile, we suppose that each user is equipped with a single radio, in the case that he cannot occupy more spectrum bands in each time slot. Taking (9) and (10) into consideration, one of the constraints in the link scheduling finally becomes,

$$\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} \sum_{i\neq j} s_{ij}^m(t) + \sum_{n\in\mathcal{M}_j\cap\mathcal{M}_q} \sum_{q\neq j} s_{jq}^n(t) \leq 1. \quad (11)$$

In addition to the above constraints at a certain user, there are also power constraints due to potential interferences among different users. Denote $s_{ij}^{mc}(t)$ as a binary indicator that describes whether the content transmission from user i to user j on band m satisfies $\Gamma_c \leq SINR_{ij}^m(t) \leq \Gamma_{c+1}(1 \leq c \leq C)$, where $c = \log_2 O$,

$$\sum_{c=1}^{C} s_{ij}^{mc}(t) \leq 1. \quad (12)$$

Moreover, since each available transmission's SINR must be above one of the thresholds in $\{\Gamma_1, \Gamma_2, \cdots, \Gamma_C\}$, we get,

$$s_{ij}^{m}(t) = \sum_{c=1}^{C} s_{ij}^{mc}(t). \quad (13)$$

Considering (3) and (4), under an adaptive M-QAM schemes, the constraint on the power P_{ij}^{m} is,

$$g_{ij}P_{ij}^{m}(t) \geq \left(\sum_{c=1}^{C} s_{ij}^{mc}(t)\Gamma_c\right)\Big(\eta_j W^m(t) + \sum\nolimits_{k\neq i, v\neq j} g_{kj}P_{kv}^{m}(t)\Big), \quad (14)$$

The other constraint on the transmission power P_{ij}^{m} is,

$$0 \leq P_{ij}^{m}(t) \leq P_{i}^{max}, \forall i, j \in \mathcal{U}, m \in \mathcal{M}_i \cap \mathcal{M}_j, \quad (15)$$

where P_i^{max} is the maximum transmission power of user i.

Besides, the amount of contents transmitted from user i to user j on band m in each time slot cannot exceed the achievable data rate multiplied by the duration of the time slot,

$$\sum_{l\in\mathcal{L}} f_{ij}^{l}(t) \leq \sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} c_{ij}^{m}(t)s_{ij}^{m}(t)\Delta t. \quad (16)$$

F. Offline Energy Consumption Minimization

In offline energy consumption minimization, we aim to minimize the **time-averaged expected** energy consumption given the interference and link scheduling constraints while guaranteeing the strong stability of the network. We formulate offline energy consumption minimization problem as,

$$\textbf{P1: minimize} \quad \lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\sum_{i\in\mathcal{U}}\mathbb{E}[E_i(t)]$$
$$\textbf{s.t.} \text{ Constraints } (8), (11), (13)\text{-}(16)$$
$$\mathbf{Q}(t) \text{ is strongly stable.} \quad (17)$$

In (17), $\mathbf{Q}(t) = \left\{Q_i^l(t), \forall i \in \mathcal{U}, l \in \mathcal{L}\right\}$. We denote the optimal result of P1 by ϕ_{P1}^{*}. Without the constraint (17), P1 is a time-coupling stochastic MINLP problem, which is already expensive to solve. Previous approaches usually solve such problems based on Dynamic Programming [10] and suffer from the "curse of dimensionality" problem. They also require detailed statistical information on the random variables in the problem, which may be difficult to obtain in practice. In addition, the constraint (17) makes P1 an even more complicated problem. Hence, we reformulate this problem into an online energy consumption optimization problem using Lyapunov optimization theory to break the time-coupling in P1 and find a feasible solution based on the current network condition.

V. Online Energy Consumption Minimization

In this section, Lyapunov optimization theory is applied to design a *drift-plus-penalty* online energy consumption minimization problem P3 without requiring any prior knowledge of the network parameters while guaranteeing the network stability. The solution to P3 depends on the current channel conditions and the current queue backlogs.

A. Equivalent Offline Optimization Problem

Before moving forward, we reformulate the offline optimization problem P1 into a new one denoted as P2 to help ensure the strong stability of the network. We will show it later. Generally, two changes have been made as follows.

To adapt to the Lyapunov optimization framework, the objective function in P1 is replaced by:

$$\overline{E} = \lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\left(\sum_{i\in\mathcal{U}}\mathbb{E}[E_i(t)] - \lambda\sum_{i\in\mathcal{U}}\sum_{l\in\mathcal{L}} v_l(t)\mathbf{1}_{i=s_l}\right), \quad (18)$$

in which λ is a parameter determined by the system controller.

Besides, we add another constraint in the following,

$$\lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\left[\sum_{l\in\mathcal{L}} f_{ij}^{l}(t)\right] \leq \lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\left[\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} c_{ij}^{m}(t)s_{ij}^{m}(t)\Delta t\right], \quad (19)$$

which is obtained by summing the inequality (16), taking expectation and limitation of both sides. The complete formulation of P2 is as follows,

$$\textbf{P2: minimize} \quad \overline{E}$$
$$\textbf{s.t.} \text{ Constraints } (8), (11), (13)\text{-}(17), (19).$$

We denote the optimal result of P2 by ϕ_{P2}^{*}.

Since λ and $v_l(t)$ in (18) are neither related to the constraints (8), (11), (13)-(16) nor the energy consumption, the new adding item $\lambda\sum_{i\in\mathcal{U}}\sum_{l\in\mathcal{L}} v_l(t)\mathbf{1}_{i=s_l}$ does not affect the optimal solution to P1. Meanwhile, if the constraint (16) is satisfied, the constraint (19) is satisfied spontaneously. Therefore, we say that the new proposed optimization problem P2 is equivalent to the problem P1. The same with P1, P2 is also a time-coupling stochastic MINLP problem which requires the prior knowledge of the network parameters. Besides, the requirement of the network stability (17) further increases its difficulty. In the following, we formulate a drift-plus-penalty problem P3 based on P2.

B. Modeling Virtual Queues

To satisfy the constraint (19), we first introduce a virtual queue $Y_{ij}(t)$ complying with the following queue law,

$$Y_{ij}(t+1) = \max\{Y_{ij}(t) - \sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} c_{ij}^{m}(t)s_{ij}^{m}(t)\Delta t, 0\} + \sum_{l\in\mathcal{L}} f_{ij}^{l}(t). \quad (20)$$

It is understood as the link-layer queue for the link from user i to his neighbor user j, describing the total amount of contents stored at user i to be transmitted to the user j at the beginning of the time slot t. Since each user transmits to at most one neighbor on one band in each time slot, the following inequality is satisfied,

$$\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} c_{ij}^m(t)s_{ij}^m(t)\Delta t-\sum_{l\in\mathcal{L}} f_{ij}^l(t)\le c_{ij}^{max}\Delta t. \quad (21)$$

Therefore, according to Lemma 2, if we guarantee the strong stability of the queue $Y_{ij}(t)$, we ensure the rate stability, i.e., constraint (16).

C. Online Finite-Queue-Aware Energy Minimization

In this subsection, we formulate an online finite-queue-aware energy consumption minimization problem. A new queue $\mathbf{\Theta}(t)=\{\mathbf{Q}(t),\mathbf{Y}(t)\}$ is introduced which is composed of the network-layer queue $\mathbf{Q}(t)=\left\{Q_i^l(t),\forall i\in\mathcal{U},l\in\mathcal{L}\right\}$ and the link-layer queue $\mathbf{Y}(t)=\{Y_{ij}(t),\forall i,j\in\mathcal{U}\}$. Suppose $\mathbf{Q}(0)=\mathbf{0}$ and $\mathbf{Y}(0)=\mathbf{0}$, we define a Lyapunov function for $\mathbf{\Theta}(t)$,

$$\begin{aligned} L\left(\mathbf{\Theta}(t)\right) &= L\left(\mathbf{Q}(t)\right)+L\left(\mathbf{Y}(t)\right) \\ &\triangleq \frac{1}{2}\left[\sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{U}}\frac{p_{s_l}^l}{p_i^l}Q_i^l(t)^2+\sum_{i\in\mathcal{U}}\sum_{j\neq i}Y_{ij}(t)^2\right], \end{aligned} \quad (22)$$

where $\frac{1}{p_i^l}Q_i^l(t)^2$ can be roughly understood as the buffer occupancy ratio of content l at user i. We multiply it by $p_{s_l}^l$ is to eliminate the parameters' effect on $L\left(\mathbf{Q}(t)\right)$ (In Section 6, we will prove that $p_{s_l}^l=\lambda V+v^{max}$).

In (22), $L\left(\mathbf{\Theta}(t)\right)$ being small implies that all queue backlogs are small, while $L\left(\mathbf{\Theta}(t)\right)$ being large implies that at least one queue backlog is large. Since all queue backlogs change with time, a key idea to push queue backlogs towards a lower congestion state is to make the queue backlogs change as small as possible. Hence, we define the one-slot conditional Lyapunov drift as,

$$\Delta\left(\mathbf{\Theta}(t)\right)\triangleq\mathbb{E}\left[L\left(\mathbf{\Theta}(t+1)\right)-L\left(\mathbf{\Theta}(t)\right)|\mathbf{Q}(t)\right], \quad (23)$$

where the expectation $\mathbb{E}(\cdot)$ is with respect to the random channel condition and depends on the control policy in reaction to these channel conditions. However, a lower queue congestion state cannot ensure limited energy consumption at users. We revise the conditional Lyapunov drift to the following drift-plus-penalty expression,

$$\Delta\left(\mathbf{\Theta}(t)\right)+V\mathbb{E}\left[\sum_{i\in\mathcal{U}}E_i(t)-\lambda\sum_{i\in\mathcal{U}}\sum_{l\in\mathcal{L}}v_l(t)\mathbf{1}_{i=s_l}|\mathbf{\Theta}(t)\right], \quad (24)$$

in which V is a positive control parameter to represent a weight on how much we emphasize on the energy consumption minimization. According to the drift-plus-penalty framework in Lyapunov optimization [11], an upper bound for (24) should be minimized in each time slot to achieve network stability while improving energy efficiency at users with the observation of the queue states $\mathbf{\Theta}(t)$, and the channel condition $c_{ij}^m(t)$ and $W^m(t)$.

Specifically, the upper bound on (23) is shown in (25) at the bottom of the next page, where $c_{ij}^{max}=W^{max}\log_2 O^{max}$ denotes the maximum capacity on the link from user i to user j. W^{max} is the maximized transmission bandwidth and O^{max} is the maximized modulation order. In the first inequality, we use the fact that $(\max\{Q-b,0\}+a)^2\le Q^2+a^2+b^2+2Q(a-b)$ for any $Q\ge 0$, $b\ge 0$, and $a\ge 0$.

According to (16), we have $\sum_{j\in\mathcal{U},j\neq i} f_{ij}^l(t)\le\sum_{j\in\mathcal{U},j\neq i}\sum_{l\in\mathcal{L}} f_{ij}^l(t)\le\sum_{j\in\mathcal{U},j\neq i}\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} c_{ij}^m(t)s_{ij}^m(t)\ \Delta t$. Since one user can transmit to at most one neighbor on at most one band in each time slot, we get $\sum_{j\in\mathcal{U},j\neq i} f_{ij}^l(t)\le\max_{j\in\mathcal{U},j\neq i} c_{ij}^{max}\Delta t$. The above explains the second inequality. Substitute (25), as shown at the top of the next page, into (23) and (24), we have,

$$\begin{aligned} \Delta\left(\mathbf{\Theta}(t)\right)+V\mathbb{E}\left[\sum_{i\in\mathcal{U}}E_i(t)-\lambda\sum_{i\in\mathcal{U}}\sum_{l\in\mathcal{L}}v_l(t)\mathbf{1}_{i=s_l}|\mathbf{\Theta}(t)\right] \\ \le B+\psi_1(t)+\psi_2(t)+\psi_3(t), \end{aligned} \quad (26)$$

where: $\psi_1(t)$: related to link scheduling variables $s_{ij}^{mc}(t)$ and transmission power $P_{ij}^m(t)$,

$$\begin{aligned} &\psi_1(t) \\ &=\mathbb{E}\left[\sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{U}}\frac{p_{s_l}^l}{p_i^l}Q_i^l(t)v_l(t)\mathbf{1}_{\mathbf{i}=\mathbf{s}_\mathbf{l}}|\mathbf{Q}(t)\right] \\ &\quad+\mathbb{E}\left[\sum_{i\in\mathcal{U}}\sum_{j\in\mathcal{U},j\neq i}(Y_{ij}(t)\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j}c_{ij}^m(t)s_{ij}^m(t)\ \Delta t)|\mathbf{Y}(t)\right] \\ &\quad+V\mathbb{E}\left[\sum_{i\in\mathcal{U}}\sum_{j\in\mathcal{U},j\neq i}\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j}P_{ij}^m(t)s_{ij}^m(t)\Delta t|\mathbf{\Theta}(t)\right]. \end{aligned} \quad (27)$$

$\psi_2(t)$: related to amount of the contents obtained from the BS $v_l(t)$,

$$\psi_2(t)=\mathbb{E}\left[\sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{U}}(\frac{p_{s_l}^l}{p_i^l}Q_i^l(t)-\lambda V)v_l(t)\mathbf{1}_{\mathbf{i}=\mathbf{s}_\mathbf{l}}|\mathbf{Q}(t)\right]. \quad (28)$$

$\psi_3(t)$: related to the amount of contents transmitted between users $f_{ij}^l(t)$,

$$\begin{aligned} \psi_3(t) &=\mathbb{E}\left\{\sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{U}}\frac{p_{s_l}^l}{p_i^l}Q_i^l(t)(\sum_{\{j|i\neq j\}}f_{ji}^l(t)\right. \\ &\qquad\left.-\sum_{j\neq i}f_{ij}^l(t))|\mathbf{Q}(t)\right\} \\ &\quad+\mathbb{E}\left[\sum_{i\in\mathcal{U}}\sum_{j\in\mathcal{U},j\neq i}\left(Y_{ij}(t)\sum_{l\in\mathcal{L}}f_{ij}^l(t)\right)|\mathbf{Y}(t)\right]. \end{aligned} \quad (29)$$

Because B is a constant, we minimize $\psi_1(t)+\psi_2(t)+\psi_3(t)$ instead of minimizing the right-hand-side of (26), where $\psi_1(t)$, $\psi_2(t)$ and $\psi_3(t)$ are conditional expectations. By using the concept of opportunistically minimizing an expectation, we minimize $\psi_1'(t)+\psi_2'(t)+\psi_3'(t)$ instead, where,

$$\psi_1'(t) = -\sum_{i\in\mathcal{U}}\sum_{j\in\mathcal{U},j\neq i} Y_{ij}(t)\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} c_{ij}^m(t)s_{ij}^m(t)\ \Delta t + V\sum_{i\in\mathcal{U}}\sum_{j\in\mathcal{U},j\neq i}\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j}(P_{ij}^m(t)s_{ij}^m(t))\Delta t, \quad (30)$$

$$\psi_2'(t) = \sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{U}}(\frac{p_{s_l}^l}{p_i^l}Q_i^l(t) - \lambda V)v_l(t)\mathbf{1}_{\mathbf{i=S_l}}, \quad (31)$$

and

$$\psi_3'(t) = \sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{U}}\frac{p_{s_l}^l}{p_i^l}Q_i^l(t)(\sum_{\{j|i\neq j\}} f_{ji}^l(t) - \sum_{j\neq i} f_{ij}^l(t)) + \sum_{i\in\mathcal{U}}\sum_{j\in\mathcal{U},j\neq i}(Y_{ij}(t)\sum_{l\in\mathcal{L}} f_{ij}^l(t)). \quad (32)$$

The final optimization problem P3 is,

$$\begin{aligned} &\textbf{P3: minimize} \quad \psi_1'(t) + \psi_2'(t) + \psi_3'(t) \\ &\textbf{s.t.}\ \text{Constraints} \quad (8), (11), (13)\text{-}(16) \\ &\mathbf{Q}(t) \text{ and } \mathbf{Y}(t) \text{ are stable}. \end{aligned} \quad (33)$$

D. A Decomposition Based Approximation Algorithm

In this subsection, we decompose P3 into three subproblems and solve them individually to obtain a suboptimal and feasible solution.

1) Link Schedule and Power Allocation: We minimize $\psi_1'(t)$ as follows by finding the optimal link scheduling and power allocation policy, determined by the variables $s_{ij}^m(t)$ and $P_{ij}^m(t)$.

$$\begin{aligned} &\textbf{S1: minimize} \quad \psi_1'(t) \\ &\textbf{s.t.}\ \text{Constraints} \quad (11), (13)\text{-}(15). \end{aligned} \quad (34)$$

S1 is a mixed integer quadratically constrained quadratic programming problem, which is also difficult to solve. We propose an iterative method in Algorithm 1. Generally, as shown in the while iteration (Line 3-11), we update power allocation profiles $P_{ij}^m(t)$ and link scheduling variables $s_{ij}^{mc}(t)$ for any $\forall i, j \in \mathcal{U}, m \in \mathcal{M}, 2^c \in \mathcal{C}$ iteratively until the objective function in S1 does not change or the maximum number of iterations is reached. We explain it in detail next.

- Fix $s_{ij}^{mc}(t)$. The main idea is to fix the values of $s_{ij}^{mc}(t)$ sequentially through a series of relaxed linear programming problems. To be specific, given $P_{ij}^m(t)$, $\forall i, j \in \mathcal{U}, m \in \mathcal{M}$, S1 becomes a binary integer programming problem. As shown in Line 4-8, a greedy algorithm is proposed. We first relax all the 0-1 integer constraints on $s_{ij}^{mc}(t)$ to $0 \le s_{ij}^{mc}(t) \le 1$, transforming the problem to a linear programming problem. Line 5 solves the linear programming problem to obtain an optimal solution with each $s_{ij}^{mc}(t)$ between 0 and 1. Among them, the

$$\begin{aligned}
&L(\mathbf{\Theta}(t+1)) - L(\mathbf{\Theta}(t)) \\
&= \frac{1}{2}\sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{U}}\frac{p_{s_l}^l}{p_i^l}\left(Q_i^l(t+1)^2 - Q_i^l(t)^2\right) + \frac{1}{2}\sum_{i\in\mathcal{U}}\sum_{j\neq i}\left(Y_{ij}(t+1)^2 - Y_{ij}(t)^2\right) \\
&= \frac{1}{2}\sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{U}}\frac{p_{s_l}^l}{p_i^l}\left[\left(\max\{Q_i^l(t) - \sum_{j\in\mathcal{U},j\neq i} f_{ij}^l(t), 0\} + (\sum_{\{j|i\neq j\}} f_{ji}^l(t) + v_l(t)\mathbf{1}_{\mathbf{i=S_l}})\right)^2 - Q_i^l(t)^2\right] \\
&\quad + \frac{1}{2}\sum_{i\in\mathcal{U}}\sum_{j\neq i}\left[\left(\max\{Y_{ij}(t) - \sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} c_{ij}^m(t)s_{ij}^m(t)\Delta t, 0\} + \sum_{l\in\mathcal{L}} f_{ij}^l(t)\right)^2 - Y_{ij}(t)^2\right] \\
&\le \frac{1}{2}\sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{U}}\frac{p_{s_l}^l}{p_i^l}\left[(\sum_{\{j|i\neq j\}} f_{ji}^l(t) + v_l(t)\mathbf{1}_{\mathbf{i=S_l}})^2 + (\sum_{j\in\mathcal{U},i\neq j} f_{ij}^l(t))^2\right] + \sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{U}}\frac{p_{s_l}^l}{p_i^l}Q_i^l(t)\left[\sum_{\{j|i\neq j\}} f_{ji}^l(t) + v_l(t)\mathbf{1}_{\mathbf{i=S_l}} - \sum_{j\in\mathcal{U},j\neq i} f_{ij}^l(t)\right] \\
&\quad + \frac{1}{2}\sum_{i\in\mathcal{U}}\sum_{j\neq i}\left(\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} c_{ij}^m(t)s_{ij}^m(t)\Delta t\right)^2 + \frac{1}{2}\sum_{i\in\mathcal{U}}\sum_{j\neq i}\left(\sum_{l\in\mathcal{L}} f_{ij}^l(t)\right)^2 + \sum_{i\in\mathcal{U}}\sum_{j\neq i} Y_{ij}(t)\left(\sum_{l\in\mathcal{L}} f_{ij}^l(t) - \sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} c_{ij}^m(t)s_{ij}^m(t)\ \Delta t\right) \\
&\le \frac{1}{2}\sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{U}}\frac{p_{s_l}^l}{p_i^l}(\max_{j\in\mathcal{U},j\neq i} c_{ij}^{max}\Delta t)^2 + \frac{1}{2}\sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{U}}\frac{p_{s_l}^l}{p_i^l}(\max_{\{j|i\neq j\}} c_{ji}^{max}\Delta t + v_l^{max})^2 + \sum_{i\in\mathcal{U}}\sum_{j\neq i}\left(c_{ij}^{max}\Delta t\right)^2 \\
&\quad + \sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{U}}\frac{p_{s_l}^l}{p_i^l}Q_i^l(t)\left[\sum_{\{j|i\neq j\}} f_{ji}^l(t) + v_l(t)\mathbf{1}_{\mathbf{i=S_l}} - \sum_{j\in\mathcal{U},j\neq i} f_{ij}^l(t)\right] + \sum_{i\in\mathcal{U}}\sum_{j\neq i} Y_{ij}(t)\left(\sum_{l\in\mathcal{L}} f_{ij}^l(t) - \sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} c_{ij}^m(t)s_{ij}^m(t)\ \Delta t\right) \\
&= B + \sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{U}}\frac{p_{s_l}^l}{p_i^l}Q_i^l(t)\left[\sum_{\{j|i\neq j\}} f_{ji}^l(t) + v_l(t)\mathbf{1}_{\mathbf{i=S_l}} - \sum_{j\in\mathcal{U},j\neq i} f_{ij}^l(t)\right] + \sum_{i\in\mathcal{U}}\sum_{j\neq i} Y_{ij}(t)\left(\sum_{l\in\mathcal{L}} f_{ij}^l(t) - \sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} c_{ij}^m(t)s_{ij}^m(t)\ \Delta t\right) \\
&\quad \text{where} \quad B = \frac{1}{2}\sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{U}}\frac{p_{s_l}^l}{p_i^l}\left(\max_{j\in\mathcal{U},j\neq i} c_{ij}^{max}\Delta t\right)^2 + \frac{1}{2}\sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{U}}\frac{p_{s_l}^l}{p_i^l}\left(\max_{\{j|i\neq j\}} c_{ji}^{max}\Delta t + v_l^{max}\right)^2 + \sum_{i\in\mathcal{U}}\sum_{j\neq i}\left(c_{ij}^{max}\Delta t\right)^2.
\end{aligned} \quad (25)$$

largest $s_{ij}^{mc}(t)$ is set to 1, denoted as $s_{i^*j^*}^{m^*c^*}(t)=1$. Due to $\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j}\sum_{i\neq j} s_{ij}^{m}(t) + \sum_{n\in\mathcal{M}_j\cap\mathcal{M}_q}\sum_{q\neq j} s_{jq} \le 1$ in the constraint (11), all the $s_{pj^*}^{nc}(t)=0$ and $s_{j^*p}^{mc}(t)=0$ for $n,m\in\mathcal{M}$, $2^c\in\mathcal{C}$ and $p,q\in\mathcal{U}$ are set to 0. The above is what Line 6 does. We remove those already fixed $s_{ij}^{mc}(t)$ from the objective functions and constraints as illustrated in Line 7. The process in Line 5-8 is repeated until all the $s_{ij}^{mc}(t)$ is obtained.

- Fix $P_{ij}^{m}(t)$. After obtaining the values of $s_{ij}^{mc}(t)$, $\forall i,j\in\mathcal{U}, m\in\mathcal{M}$, S1 becomes a linear programming problem with constraints (14)-(15), which can be easily solved.
- Update $\psi_1'(t)^{(n+1)}$ given all $P_{ij}^{m}(t)^{(n+1)}$ and $s_{ij}^{mc}(t)^{(n)}$.

As in Line 6, band m is allocated to one transmission link in time slot t, say, from user i^* to user j^*. All the other users who want to offload contents to user i^* and j^* or request contents from user i^* and j^* on band m are not allowed. Since we get a number of the $s_{ij}^{mc}(t)$ values in each "inside" while iteration, Line 6 simplifies the solving process for S1. In addition, due to the interference constraints, allowing many user pairs (e.g., user i to user j, user k to user v) to occupy the same band is impossible in order to ensure the successful transmission. Hence, the complexity of Algorithm 1 does not increase as the number of users increases. It does not suffer from the issue "curse of dimensionality". The complexity of Algorithm 1 is the same as the complexity of linear programming. Whereas previous approaches applying Dynamic Programming always suffers from the "curse of dimensionality" problem [10].

Algorithm 1 Link Scheduling and Power Allocation

Input: $c_{ij}^{m}(t)$, $\mathbf{Y}(t)$, V, ϵ, Num
Output: $s_{ij}^{mc}(t)$, $P_{ij}^{m}(t)$ for $m\in\mathcal{M}$, $2^c\in\mathcal{C}$ and $i,j\in\mathcal{U}$
1 Choose an initial value for $\psi_1'(t)^{(0)}$, $\psi_1'(t)^{(1)}$ and $P_{ij}^{m}(t)^{(0)}$;
2 Set $n=0$
3 **while** $|\psi_1'(t)^{(n+1)}-\psi_1'(t)^{(n)}|<\epsilon$ *or* $n+1>$ *Num* **do**
4   **while** *there exists one* $s_{ij}^{mc}(t)^{(n)}$ *that is not fixed as* 0 *or* 1 **do**
5   Solving $S1$ by relaxing all $s_{ij}^{mc}(t)^{(n)}$ as $0\le s_{ij}^{mc}(t)^{(n)}\le 1$ for any $m\in\mathcal{M}$, $2^c\in\mathcal{C}$ and $i,j\in\mathcal{U}$ given $P_{ij}^{m}(t)^{(n)}$.
6   Set the largest $s_{ij}^{mc}(t)^{(n)}$ to 1. Denote as $s_{i^*j^*}^{m^*c^*}(t)^{(n)}=1$ Based on (11), set $s_{pj^*}^{nc}(t)^{(n)}=0$ and $s_{j^*p}^{mc}(t)^{(n)}=0$ for any $n,m\in\mathcal{M}$, $2^c\in\mathcal{C}$ and $p,q\in\mathcal{U}$
7   Given already fixed $s_{ij}^{mc}(t)^{(n)}$ for $m\in\mathcal{M}$, $2^c\in\mathcal{C}$ and $i,j\in\mathcal{U}$, update $S1$.
8   **end**
9   Calculate $P_{ij}^{m}(t)^{(n+1)}$ by solving $S1$ given all $s_{ij}^{mc}(t)^{(n)}$.
10   Calculate $\psi_1'(t)^{(n+1)}$ given all $P_{ij}^{m}(t)^{(n+1)}$ and $s_{ij}^{mc}(t)^{(n)}$.
11 **end**

2) Content Allocation: We minimize $\psi_2'(t)$ by finding representative users together with the amount of the contents they obtain from the BS,

$$\textbf{S2: minimize}\quad \psi_2'(t) \qquad \textbf{s.t. } \text{Constraints}\quad 0\le v_l(t)\le v^{max}. \tag{35}$$

A search algorithm is developed to achieve the content allocation. To be specific, at the beginning of each time slot, given the queue backlogs $Q_i^l(t)$ for each content l, the user with the smallest queue backlog is chosen as the representative. When there are multiple users with the same smallest queue backlog, we randomly pick one of them as the representative user. Therefore, the amount of contents he can get is determined by,

$$v_l(t)=\begin{cases} v^{max} & \text{if}\quad Q_{s_l}^l(t)-\lambda V\le 0\\ 0 & \text{otherwise.}\end{cases} \tag{36}$$

3) Routing: In this subsection, we minimize $\psi_3'(t)$ by finding the optimal routing policy, i.e., determining the variables $f_{ij}^l(t)$. By reorganizing (32), we have,

$$\psi_3'(t)=\sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{U}}\sum_{j\in\mathcal{U}}\left(-\frac{p_{s_l}^l}{p_i^l}Q_i^l(t)+\frac{p_{s_l}^l}{p_j^l}Q_j^l(t)+Y_{ij}(t)\right)f_{ij}^l(t). \tag{37}$$

Hence, the optimization problem becomes,

$$\textbf{S3: minimize}\quad \psi_3'(t) \qquad \textbf{s.t. } \text{Constraints}\quad (8),\quad (16). \tag{38}$$

The objective function of S3 can be viewed as a weighted sum of the variables $f_{ij}^l(t)$. Hence, we can determine $f_{ij}^l(t)$ at user i locally based on the current queue backlogs $\frac{p_{s_l}^l}{p_i^l}Q_i^l(t)$, $\frac{p_{s_l}^l}{p_j^l}Q_j^l(t)$ and $Y_{ij}^l(t)$. An algorithm is proposed described in Algorithm 2.

In Line 1, the variables $f_{ij}^l(t)$ $(\forall j=s_l, l\in\mathcal{L})$ are set to 0 according to constraint (8). Line 2-9 and line 11 are to set the variables $f_{ij}^l(t)$ $(\forall i,j\in\mathcal{U}, l\in\mathcal{L})$. Specifically, the variables $f_{ij}^l(t)$ $(\forall j\in\mathcal{U}, l\in\mathcal{L})$ with non-negative coefficients are set to 0 in line 3-4. The variable $f_{ij}^l(t)$ with the smallest coefficient is found in Line 9. The value for $f_{ij}^l(t)$ is fixed in line 10-14. Because it is possible that $\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} c_{ij}^m(t)s_{ij}^m(t)\Delta t$ is equal to 0 if $\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} s_{ij}^m(t)=0$. In that case, the corresponding variable $f_{ij}^l(t)$ is set to 0. Otherwise, $f_{ij}^l(t)$ with the smallest coefficient is set to $\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} c_{ij}^m(t)s_{ij}^m(t)\Delta t$. It means that the transmission link from user i to user j is fully utilized to deliver the requested contents. Note that if there are multiple variables $f_{ij}^l(t)$ with the same smallest coefficients, the user i randomly picks one of them and sets it to $\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} c_{ij}^m(t)s_{ij}^m(t)\Delta t$.

In each time slot, the online finite-queue-aware energy consumption minimization problem is solved after S1, S2 and S3 are solved respectively. The queues $\mathbf{Q}(t)$ and $\mathbf{Y}(t)$ are then updated according to (7) and (20), respectively. We denote the corresponding time-averaged expected total energy consumption by ϕ_{P3}^*.

Algorithm 2 Routing

Input: $\mathbf{Q}(t)$, $\mathbf{Y}(t)$, p_i^l for any $l \in \mathcal{L}$ and $i \in \mathcal{U}$
Output: $f_{ij}^l(t)$ for any $l \in \mathcal{L}$ and $i, j \in \mathcal{U}$

```
Set f^l_{j s_l}(t) = 0 for any j ∈ U
foreach l ∈ L and i, j ∈ U do
    if ( -(p^l_{s_l}/p^l_i) Q^l_i(t) + (p^l_{s_l}/p^l_j) Q^l_j(t) + Y_ij(t) ) ≥ 0 then
        f^l_ij(t) = 0
    else
        Calculate
        coe^l_ij(t) = ( -(p^l_{s_l}/p^l_i) Q^l_i(t) + (p^l_{s_l}/p^l_j) Q^l_j(t) + Y_ij(t) ).
    end
end
Find the smallest coe^l_ij(t). Denote corresponding f^l_ij(t)
    as f^{l*}_{i* j*}(t)
if Σ_{m ∈ M_i ∩ M_j} s^m_{i* j*}(t) = 0 then
    Set f^{l*}_{i* j*}(t) = 0
else
    Set f^{l*}_{i* j*}(t) = Σ_{m ∈ M_i ∩ M_j} c^m_{i* j*}(t) s^m_{i* j*}(t) Δt
end
Set other f^l_ij(t) = 0 for any l ∈ L and i ∈ U
```

VI. Performance Analysis

In this section, we prove that the proposed approximation algorithm guarantees network strong stability. Following that, we derive both the lower and upper bounds on the optimal result of P1. Finally, we give some simulation results based on our proposed approach.

A. Network Strong Stability

Our proposed approach finds an approximation solution to P3 which satisfies the constraints (8), (11), (13)-(16). However, we do not consider the network strong stability, which is an important and challenging problem.

Theorem 1: Our proposed approximation problem guarantees that the queues $\mathbf{Q}(t)$ and $\mathbf{Y}(t)$ are all strongly stable. □

Proof: First, we demonstrate the strong stability of $\mathbf{Q}(t)$ by considering an arbitrary queue $Q_i^l(t)$. In particular, the induction method is deployed to prove that $Q_i^l(t) \leq p_i^l$, where $p_{s_l}^l = \lambda V + v^{max}$ and $p_i^l = (1 + \alpha \rho_i^l) p_{s_l}^l$.

When $t = 0$, we have $Q_i^l(0) = 0 \leq p_i^l$.

When $t = t'(t' \geq 0)$, we suppose $Q_i^l(t') \leq p_i^l$. We prove that $Q_i^l(t'+1) \leq p_i^l$ in the following.

Situation 1: $i = s_l$. The queuing law (7) becomes,

$$Q_{s_l}^l(t+1) = \max\{Q_{s_l}^l(t) - \sum_{j \in \mathcal{U}, j \neq i} f_{s_l j}^l(t), 0\} + v_l(t). \tag{39}$$

We consider two situations on the value of $v_l(t)$,

- Case 1: $Q_{s_l}^l(t) \leq \lambda V$. According to (36), $v_l(t) = v^{max}$. $Q_{s_l}^l(t'+1) \leq Q_{s_l}^l(t') + v^{max} \leq \lambda V + v^{max} = p_{s_l}^l$.
- Case 2: $Q_{s_l}^l(t) > \lambda V$. According to (36), $v_l(t) = 0$. $Q_{s_l}^l(t'+1) \leq Q_{s_l}^l(t') \leq \lambda V + v^{max} = p_{s_l}^l$,

Situation 2: $i \neq s_l$. The queuing law of $Q_i^l(t)$ is,

$$Q_i^l(t+1) = \max\left\{Q_i^l(t) - \sum\nolimits_{j \in \mathcal{U}, j \neq i} f_{ij}^l(t), 0\right\} + \sum\nolimits_{\{j | i \in \mathcal{U}, i \neq j\}} f_{ji}^l(t). \tag{40}$$

Since only one neighboring user can transmit to user i in time slot t, we denote him as user j. Considering the coefficient before $f_{ji}^l(t)$ in the objective function of S3, two situations are discussed:

- Case 1: $\frac{p_{s_l}^l}{p_i^l} Q_i^l(t) < \frac{p_{s_l}^l}{p_j^l} Q_j^l(t) - Y_{ji}(t)$. According to (40), $Q_i^l(t+1) \leq Q_i^l(t) + f_{ji}^l(t) \leq \frac{p_i^l}{p_j^l} Q_j^l(t) - \frac{p_i^l}{p_{s_l}^l} Y_{ji}(t) + f_{ji}^l(t) \leq \frac{p_i^l}{p_j^l} Q_j^l(t) \leq p_i^l$. The third inequality is satisfied due to the following reasons,
  - $Y_{ji}(t) = 0$. Based on the solution to S1, $s_{ji}^{mc}(t) = 0$ and thus $f_{ji}^l(t) = 0$. The inequality holds.
  - $Y_{ji}(t) \geq 1$. Since $f_{ji}^l(t) \leq \max\limits_{i \in \mathcal{U}, j \neq i} c_{ij}^{max} \Delta t$ and $\frac{p_i^l}{p_{s_l}^l} \geq 1$, we have $\frac{p_i^l}{p_{s_l}^l} Y_{ij}(t) \geq f_{ji}^l(t)$. The inequality is satisfied.
- Case 2: $\frac{p_{s_l}^l}{p_i^l} Q_i^l(t) \leq \frac{p_{s_l}^l}{p_j^l} Q_j^l(t) - Y_{ji}(t)$. Based on the solution to S3, $f_{ji}^l(t) = 0$. Following (40), we get $Q_i^l(t+1) \leq Q_i^l(t) \leq p_i^l$.

From the above proof, an arbitrary queue $Q_i^l(t)$ is finite in each time slot. With Definition 2 $\mathbf{Q}(t)$ is strongly stable.

Next, we prove the strong stability of $\mathbf{Y}(t)$ by considering an arbitrary queue $Y_{ij}(t)$. In particular,

$$Y_{ij}(t) \leq \max_{0 \leq k \leq t} \sum_{l \in \mathcal{L}} f_{ij}^l(k). \tag{41}$$

When $t = 0$, $Y_{ij}(0) = 0 \leq \max\limits_{0 \leq k \leq t} \sum_{l \in \mathcal{L}} f_{ij}^l(k)$.

When $t = t'(t' \geq 0)$, we suppose $Y_{ij}(t') \leq \max\limits_{0 \leq k \leq t} \sum_{l \in \mathcal{L}} f_{ij}^l(k)$. We prove that $Y_{ij}(t'+1) \leq \max\limits_{0 \leq k \leq t'+1} \sum_{l \in \mathcal{L}} f_{ij}^l(k)$ in the following.

- Case 1: $Y_{ij}(t) \leq \sum\limits_{m \in \mathcal{M}_i \cap \mathcal{M}_j} c_{ij}^m(t) s_{ij}^m(t) \Delta t$. Based on (20), $Y_{ij}(t+1) = \sum_{l \in \mathcal{L}} f_{ij}^l(t) \leq \max\limits_{0 \leq k \leq t+1} \sum_{l \in \mathcal{L}} f_{ij}^l(k)$.
- Case 2: $Y_{ij}(t) > \sum\limits_{m \in \mathcal{M}_i \cap \mathcal{M}_j} c_{ij}^m(t) s_{ij}^m(t) \Delta t$. Based on (20), $Y_{ij}(t+1) = Y_{ij}(t) - \sum\limits_{m \in \mathcal{M}_i \cap \mathcal{M}_j} c_{ij}^m(t) s_{ij}^m(t) \Delta t + \sum\limits_{l \in \mathcal{L}} f_{ij}^l(t)$. With inequality (16), $Y_{ij}(t+1) \leq Y_{ij}(t) \leq \max\limits_{0 \leq k \leq t} \sum_{l \in \mathcal{L}} f_{ij}^l(k) \leq \max\limits_{0 \leq k \leq t+1} \sum_{l \in \mathcal{L}} f_{ij}^l(k)$

Because $\sum_{l \in \mathcal{L}} f_{ij}^l(t) \leq c_{ij}^{max} \Delta t$, we have $Y_{ij}(t) \leq c_{ij}^{max} \Delta t$. Therefore, $\mathbf{Y}(t)$ is always finite and strongly stable. □

B. Lower and Upper Bounds for P1

In this subsection, we obtain both lower and upper bounds for the optimal results of P1, i.e., ϕ_{P1}^*.

Theorem 2: The solution obtained from our proposed algorithm serves as a suboptimal solution to P1.

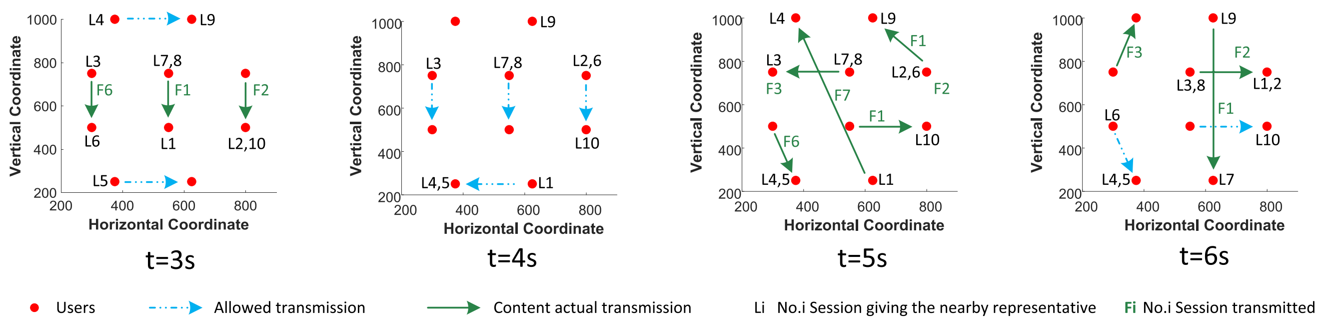

Fig. 2. Dynamic characteristics

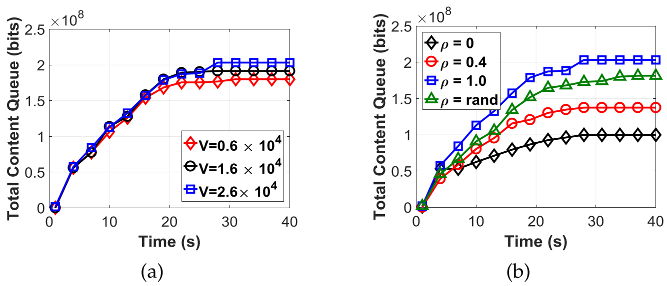

Fig. 3. Content queue performance. (a) Energy Weight Controller V Effect. (b) User's Interest ρ Effect.

And the corresponding time-averaged expected energy consumption holds an upper bound on the optimal result of P1, i.e., $\phi^*_{P1} \leq \phi^*_{P3}$. □

Proof: Our proposed algorithm finds a feasible solution to P3 in each time while satisfying all the constraints, e.g., (8), (11), (13)-(16) and (33). In addition, because (16) is satisfied and $\mathbf{Y}(t)$ is strongly stable as proved above, $\mathbf{Y}(t)$ is rate stable according to the Lemma 2. Hence, the constraint (19) holds as well. The solution in P3 is a feasible solution to P2. Because the problems P1 and P2 are equivalent, the solution in P3 is also a feasible solution to P1. The corresponding time-averaged expected energy consumption holds an upper bound on the optimal result of P2, i.e., $\phi^*_{P3} \geq \phi^*_{P1}$. □

Next, we find a lower bound on ϕ^*_{P1} as in Theorem 3.

Theorem 3: The time-averaged expected energy consumption minimized by optimally solving P3, denoted by ϕ^*_{P3}, is within a constant gap $\frac{B}{V}$ from the time-averaged expected energy consumption achieved by P2, i.e., ϕ^*_{P1}. Specifically, we obtain,

$$\phi^*_{P3} - \frac{B}{V} \leq \phi^*_{P1},$$

in which B and V are defined in previous sections. □

Proof: Please refer to Appendix A for the detailed proof. □

According to the Theorem 2 and the Theorem 3, we get a lower bound and an upper bound on the optimal result of P1, respectively, where,

$$\phi^*_{P3} - \frac{B}{V} \leq \phi^*_{P1} \leq \phi^*_{P3}. \tag{42}$$

Because B and V are independent, $\frac{B}{V}$ definitely goes to 0 as V increases. Thus, the gap between the upper and lower bound definitely becomes smaller. Thus, we could totally prove its sub-optimality theoretically.

TABLE II
SIMULATION SETTINGS

Parameter	Values
Area	$1000m \times 1000m$
Number of Users	10
Number of Time Slots	40
Duration in each time slot	1s
Bandwidth	$[1.2, 1.4, 1.6]\ MHz$
Modulation Strategy	$[2^3, 2^4, 2^5]$QAM
Bit Error Rate	10^{-3}
SINR Thresholds	$\{24.73, 52.98, 109.50\}$
Max. Transmission Power	2W
Noise Power Density	10^{-20}W/Hz
Path Loss	4
Weight V	4.6×10^4
User's Interest ρ	1

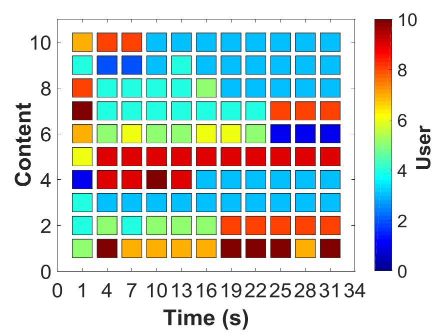

Fig. 4. Representative choice.

C. Simulation Results

We evaluate the performance of our proposed approximation approaches in MATLAB on a computer with 4.0 GHz CPU and 32GB RAM. All the parameters are set in Table. II. Specifically, users are located at $(375, 250)$, $(625, 250)$, $(300, 500)$, $(550, 500)$, $(800, 500)$, $(300, 750)$, $(550, 750)$, $(800, 750)$, $(375, 1000)$ and $(625, 1000)$ respectively as shown in Fig. 2.

1) Content Queue Performance: Fig. 3 demonstrates the changes in content queue amount as time goes by. In each time slot, we sum up the content queue amount for each session at each user as the total one, which is dynamic and arrives at a stable state after a period of less than 30s. Such observation is consistent with the analysis in subsection 6.1. Thus, in the following simulations, we consider the time slots from 1 to 30 instead of 40. Besides, we check the effect on the content queue brought by the energy weight controller and the user's interest respectively. In Fig. 3a, the total content queue varies slightly under different energy weight controller. It is mainly because we factitiously initialize the content queue amount to

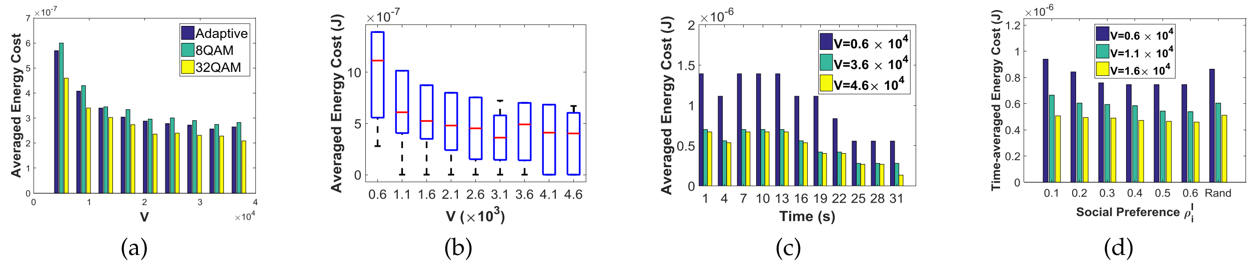

Fig. 5. Energy cost performance. (a) Modulation effect. (b) Energy weight V effect. (c) Time effect. (d) Social effect.

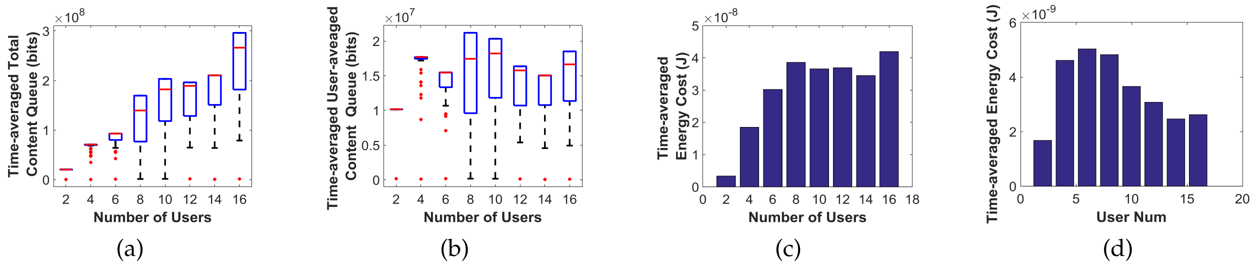

Fig. 6. User number effect. (a) Total content queue. (b) Averaged content queue. (c) Total energy cost. (d) Averaged energy cost.

be proportional to the energy weight controllers. On the other hand, the user's interest in the content session puts a positive effect on the content queue. If a user is more interested in each content, he would like to store contents and popularize them at the same time. Thus, he allows more contents to be kept in his queue. As can be seen in Fig. 3b, at the stable state, the total content queue is maximized when $\rho = 1.0$.

2) Dynamic Characteristics: The dynamic content queue in Fig. 3 introduces the dynamic performance to the whole system. Such dynamic characteristics are reflected on the representative user choice ($\mathbf{1_{i=S_l}}$) directly according to (36). As shown in Fig. 4, in each time slot, different representative users are chosen to receive different content sessions from the service provider. Meanwhile, the same content session is transmitted to different representative users in different time slots. As time goes by, the choice of different representative users becomes stable (from 25s to 31s), which indicates the stability of the entire system is reached.

Besides, we describe the dynamic content transmission choice from the time slot 3 to the time slot 6 in Fig. 2. The allowed and the actual content transmission pairs ($s_{ij}^m(t)$ and $f_{ij}^l(t)$) change in different time slots. In some time slots, e.g., the time slot 4, no contents are transmitted although a few transmission pairs are allowed. Whereas the contents are transmitted in all the allowed transmission pairs in some time slot, e.g., the time slot 5. Meanwhile, different content sessions are transmitted between different transmission pairs in different time slots. The dynamic content queue affects the offloading content amount as in **S3**, which puts an effect on both the content queue and the virtual queue like. The dynamic virtual queue affects the choice of the allowed transmission pairs as in **S2**. Thus, the system becomes dynamic but finally arrives at a stable state.

3) Energy Cost Performance: We consider the averaged energy cost for each user in each time in Fig.5. Fig. 5a shows the effect on the averaged energy cost brought by different modulation schemes. To achieve content successful transmission under random channel conditions, users have to choose different modulations schemes adaptively. Therefore, we see that the averaged energy cost under the adaptive M-QAM scheme is lower than that under 8QAM and higher than that under 32QAM.

Fig. 5b considers the averaged energy cost in time slot 2. As can be seen, the averaged energy cost decreases with the increase of the energy weight controller, which is consistent with our description previously. Fig. 5c shows the changes in the averaged energy cost as the time goes by, from which the average energy cost becomes almost the same after 20 time slots. The dynamic averaged energy cost performance is the same as that of the content queue amount. Besides, we demonstrate the time-averaged energy cost under users' social preferences in Fig.5d, where "Rand" means users have different interests in different contents. Users would like to cache their interested contents instead of disseminating them, especially in bad channel conditions. Therefore, we see that the time-averaged energy cost decreases with the increase of social preference. Meanwhile, as energy weight controller V increases, the difference of time-averaged energy cost between social preferences becomes smaller in Fig.5d. Social preference's effect on the energy cost results from its effect on the maximum queue size. When V becomes larger, keeping queue stability becomes less important. Users could cache more contents no matter how much they are interested in the contents. Hence, the total energy cost is lowered. Besides, social preference's effect on the energy cost becomes subtle. When V becomes smaller, users have to strictly guarantee their queue stability. They could not cache too much in their buffers. Therefore, they have to offload more contents to other users, which increases the energy cost. Meanwhile, due to the strict requirement to queue stability, users cache their most interested contents. Thus, their social preferences will greatly affect the energy cost.

4) User Number Effect: Besides the above consideration, we compare the content queue and energy cost performance

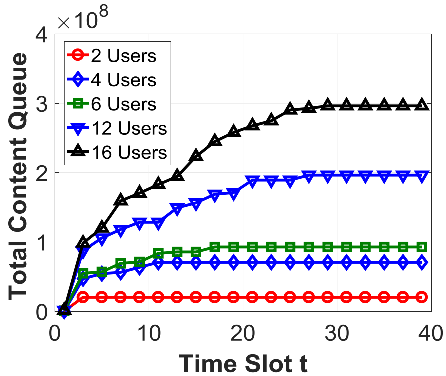

Fig. 7. Reaching steady state speed.

under a different number of users. Specifically, we consider the cases with 2, 4, 6, 8, 10, 12, 14 and 18 users respectively. The minimum distance among users in each case is set to 250m. In Fig.6a, we consider the time-averaged total content queues, where the content queue amount increases as the number of users increases. In Fig. 6b, we further average the content queue over the user number. The time-averaged user-averaged content queue jumps among the cases with different numbers, which indicates the introduction of more users does not affect the stability of the content queue. In addition to time-averaged total content queue performance, the time-averaged energy cost also increases with the introduction of more users whereas per-user time-averaged energy cost decreases, which are shown in Fig. 6c and 6d respectively.

Finally, we investigate our solution's speed to a steady network state. As shown in Fig.7, when a few users exist, they can reach a steady network state very soon. When the number of users increases, it takes a longer time to reach a steady state. Since users are always in a changing environment, the speed of reaching a network state does not affect users to offload or to access data as long as they do not reach the maximum queue size. Such observations further demonstrate that our proposed online optimization solution is not affected by the number of users, which means our solution does not suffer from the "curse of dimensionality".

VII. Conclusion

In this paper, we propose a social-aware energy-efficient data offloading approach to reduce energy consumption and achieve green communication in the cellular network. By jointly considering storage capacity allocation, queuing and transmission scheduling, we design an offline energy consumption minimization problem, which is a time-coupling stochastic MINLP problem. By introducing a virtue queue and employing Lyapunov drift-plus-penalty theory, we reformulate the problem as an online finite-queue-aware energy consumption problem, which is decoupled and then decomposed into several separate subproblems in each time slot. The proposed method ensures the network with strong stability. Both lower and upper bounds on the optimal result of the original optimization problem are obtained. Based on the simulation results, we show the feasibility and efficiency of our approximation approach.

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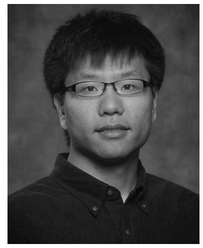

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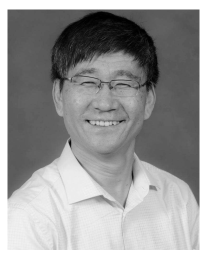

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