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Stochastic Optimization in Cooperative Relay Networks for Revenue Maximization

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Abstract: In cellular networks, cooperative relaying is an economic and promising way to enlarge the network capacity and coverage. In the case that multiple users and multiple relays are taken into account, efficient resource allocation is important in such networks. In this paper, we consider the joint relay power control with amplify-and-forward (AF) strategy and dynamic pricing for uplink cellular networks in order to maximize the network administrator's system revenue. The system revenue is associated with pricing strategies and mobile users' random data request, which is supported by the relay assisted transmission. To deal with the problem of the coupling in pricing and relay resource allocation, we utilize Lyapunov optimization techniques to design online pricing and relay power control without any statistic information of random events in networks. Theoretical analysis shows that the proposed algorithm can achieve a near-optimal performance and simulation results also validate its effectiveness and robustness.
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0 Introduction

Recently, cooperative relay architecture has been a hot issue drawing abroad attention because of its better quality of service (QoS) for cellular users, especially for those at the cell edge. It enhances system throughput and network coverage by taking advantage of broadcasting nature and spatial diversity. Hence cooperative relaying has been considered as a promising technology in the next generation networks. To meet the increasing need of bandwidth intensive service, efficient radio resource allocation schemes are proposed in the cooperative relaying networks. In this paper we study the resource allocation problem for cooperative relay networks from the network administrator's perspective. The network administrator's targets are not only to maximize its own revenue in the relay networks but also to satisfy each mobile user's data rate request. Considering the network economic issue and accommodate mobile users' time-varying rate requirement, we propose a joint dynamic pricing and relay resource allocation scheme.

Significant research effort has been devoted to take a system view of the cooperative relay networks and try to optimize the cross-layer network performance. Reference [1] studied relay selection and power allocation for amplify-and-forward based two-way relay networks (TWRN) with asymmetric traffic requirements (ATR). Instead of the centralized scheme in Ref. [1], Ref. [2] jointly designed flow control, relay selection and power allocation for multi-hop relay networks in a distributed way. In terms of quality of service, Ref. [3] investigated the outage probability bound of joint relay selection and power allocation for two-way relay channels (TWRC). In light of user and channel diversity, Ref. [4] first proposed flexible channel cooperation (FLEC), a novel flexible channel cooperation scheme, where relay techniques were used to facilitate spectrum sharing in cognitive radio networks. A relay resource allocation problem was investigated in Ref. [5] based on the Nash bargaining solution over wireless amplify-and-forward (AF) relay networks. In time-varying environments, the relay scheduling problem becomes complicated due to mobile users' random data requirement and stochastic channel state information. To tackle the problem, Ref. [6] proposed a novel scheme for delay-optimal scheduling in multi-user multi-relay cellular wireless networks with the help of Markov decision process (MDP). On the other hand, several works[7-9] turned to Lyapunov optimization method[10]

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to optimize the long-term network throughput or stability for relay networks. The salient difference between MDP formulation and Lyapunov optimization framework is that the MDP method incorporates the system state transition probability and thus it can result in a smaller queueing delay compared with Lyapunov optimization method. As for Lyapunov optimization, it converts time average form problem formulation to a series of optimization problems with each network state instead and reduces the computational complexity by avoiding calculating long-term data. Thus, there is no prior knowledge on statistics event needed in Lyapunov optimization method.

In this paper, we consider the uplink cellular transmission assisted by multiple relays with AF relaying strategy and space-time coding. The remarkable difference between this paper and previous works is that we consider each mobile user's service requirement can be effected by the data price, which is a more realistic scenario. Then the network administrator can use price to execute the network flow control and gain revenue simultaneously. Compared with the pricing algorithms in Refs. [11-12] where the aim is to maximize the instantaneous network revenue, this paper jointly takes into account relay resource allocation and price setting to maximize the average network revenue, which is more appropriate for highly dynamic networks. Reference [13] proposed a pricing-based cross-layer scheduling scheme for cognitive radio networks. Dynamic pricing schemes were also proposed by Refs. [14-15] for stochastic wireless fidelity (WiFi) networks and multi-hop wireless networks, respectively. Compared with the above works, our work further considers energy conservation issue for relay networks in addition to different scenarios.

In summary, this paper has the following contributions:

(1) From the network administrator's point of view, we formulate the dynamic pricing algorithm for revenue maximization problem as well as energy saving issues in cooperative relay networks.

(2) A price-based congestion control and relay power allocation are jointly designed using Lyapunov optimization. This algorithm can operate using the current situation of the network state instead of knowing any statistic information of stochastic events, such as random packet arrival and channel fading state, and computing long-term statistics yet still obtain provably-efficient performance and guarantee the network stability.

(3) We provide a rigorous analysis to prove that the actual system revenue can be close to the optimal value arbitrarily at the expense of increased queueing delay, even without knowing the statistic information in the network.

1 System Model and Problem Formulation

1.1 Physical Layer Model

We consider the uplink transmission in a two-hop relay assisted network, which consists of K mobile users. There are M relays that use the AF cooperative strategy to help the K mobile users to transmit to destinations. The set of users is denoted as $\kappa = \{1, 2, \cdots, K\}$ and the set of relays is $\mathcal{M} = \{1, 2, \cdots, M\}$. Each relay can help multiple users to transmit under the relay's power constraint, and multiple relays can assist destinations to obtain the information from mobile users. The total bandwidth is assumed to be divided into multiple channels with equal bandwidth, and each user is allocated one channel for its data transmission. The time-division multiplexing is used by AF cooperative diversity for each transmission, since each relay works in the half-duplex manner and it cannot receive and transmit the users' message at the same time. It means that in the first time slot, the source of each user uses the allocated channel to transmit data to the relays and the destination, and in the second time slot, the relays forward the received data to the destination. It is assumed that an ideal distributed space time coding is adopted by the relays and multiple relays for a particular user can forward the received data to that user's destination on the same channel simultaneously. We assume that the data transmissions for the user in the first time slot and for the relays in the second time slot are perfectly synchronized with each other to correctly receive the signal. In the first time slot, the signal to noise ratio (SNR) of the channel which transmit from user k to its destination is

$$\gamma_{s_k,d_k} = \frac{P_{s_k} H_{s_k,d_k}}{\sigma^2}, \tag{1}$$

where P_{s_k} is the user k's transmission power, H_{s_k,d_k} is the channel gain between the source s_k and the destination d_k, and σ^2 is the noise variance, which is assumed to be independent and identically distributed (i.i.d) in each channel. Without loss of generality, we assume that the value of channel condition remains constant during one time slot and changes between any two time slots. With the assistance of relay m by AF relaying strategy, the received signal at relay $m\,(r_m)$ from user k is:

$$X_{s_k,r_m} = \sqrt{P_{s_k} H_{s_k,r_m}} Y_{s_k} + \alpha_{s_k,r_m}, \tag{2}$$

where Y_{s_k} represents the broadcast signal from source k, H_{s_k,r_m} is the channel gain from source k, and $\alpha_{s_k,r_m} \sim N(0, \sigma^2)$. In the second time slot, relay m forward the information to the destination and the received signal X_{r_m,d_k} is:

$$X_{r_m,d_k} = \sqrt{P_{r_m,d_k} H_{r_m,d_k}} Y_{r_m,d_k} + \alpha_{r_m,d_k}, \tag{3}$$

where P_{r_m,d_k} is the transmit power at relay m for user k, H_{r_m,d_k} is the channel gain between relay m to the destination of user k, and

$$Y_{r_m,d_k} = \frac{X_{s_k,r_m}}{|X_{s_k,r_m}|} \tag{4}$$

is the transmitted signal from relay m to the destination of user k. According to the above equations, we substitute Eqs. (2)—(4), and rewrite Eq. (3) as:

$$X_{r_m,d_k} = \frac{\sqrt{P_{r_m,d_k}H_{r_m,d_k}}\left(\sqrt{P_{s_k}H_{s_k,r_m}}Y_{s_k} + \alpha_{s_k,r_m}\right)}{\sqrt{P_{s_k}H_{s_k,r_m} + \sigma^2}}. \tag{5}$$

Based on Eq. (5), we can derive the relayed SNR for source k with the help of relay m:

$$\gamma_{s_k,r_m,d_k} = \frac{P_{s_k}P_{r_m,d_k}H_{s_k,d_k}H_{r_m,d_k}}{\sigma^2(P_{s_k}H_{s_k,d_k} + P_{r_m,d_k}H_{r_m,d_k} + \sigma^2)}. \tag{6}$$

Eventually, the rate at the destination k with the help of relay m is given by

$$C_{s_k,r_m,d_k} = \frac{1}{2}W\,\mathrm{lb}(1 + \gamma_{s_k,d_k} + \gamma_{s_k,r_m,d_k}),$$

where W is the channel bandwidth and "1/2" is due to the half-duplex constraint of each relay. Let $R(k)$ denote the set of relays that are available to help user k. The rate from user k to destinations with the help of multiple relays is

$$C_k = \frac{1}{2}W\,\mathrm{lb}\Big(1 + \gamma_{s_k,d_k} + \sum_{m\in R(k)}\gamma_{s_k,r_m,d_k}\Big). \tag{7}$$

1.2 Queueing Model

We assume that $A_k(t)$ stands for the random requested data rate of user k at the end of time slot t waiting for transmission to the destination. Since the transmission between the source and destination may not be always satisfied, this leads to data accumulation at users. Each user's packets are stored in one of the K data queues corresponding to each destination before they can be sent to the destinations. The packet arrival process $A_k(t) \in [0, A_k^{\max}]$ is assumed to be i.i.d over each time slot and $E[A_k(t)] = \lambda_k$. Among the arrival packets, only $R_k(t)$ of $A_k(t)$ are admitted into each user's buffer with queue length $Q_k(t)$ in time slot t, which is adjusted according to the dynamical pricing policy that will be specified later. All the admission rate vectors that can be supported by the network are called the network capacity region, which is also known as network stability region[10]. The data queue of each user k is updated as

$$Q_k(t+1) = (Q_k(t) - C_k(t))^+ + R_k(t), \quad \forall k \in \kappa, \tag{8}$$

where $(x)^+ = \max\{0, x\}$, and $C_k(t)$ is the service rate of user k, which is given in Eq. (7). Specifically, let Eq. (8) have its initial value of zero and update the queue at each time slot.

During time slot t, the base station (BS) representing the network administrator charges each user an admission price $q_k(t)$ per unit data rate. The price plays the role of not only controlling the admitted flows, but also, more significantly, establishing system-wide revenue from the network's perspective. We assume that each user have an increasing, differentiable and concave utility function $U_k(y_k)$, which reflects its degree of satisfaction when it has the admitted rate y_k. At time slot t, user k selects an admitted data rate which maximizes its net income:

$$R_k(t) = \arg\max_{y_k\in[0,A_k(t)]}(U_k(y_k(t)) - q_k(t)y_k(t)), \quad \forall k \in \kappa. \tag{9}$$

In this paper, $U_k(y_k(t))$ is assumed to be a logarithmic function, i.e., $U_k(y_k(t)) = \lg(1 + y_k(t))$. Here we should emphasize that the following analysis can be extended to other forms of utility functions straightforwardly. To guarantee the minimum data rate requirement of different users, we construct the virtual service queue $Z_k(t)$ with its dynamics given by:

$$Z_k(t+1) = (Z_k(t) - R_k(t))^+ + a_k, \quad \forall k \in \kappa, \tag{10}$$

where the initial value of $Z_k(t)$ is set to zero. Denote $\boldsymbol{a} = (a_1, a_2, \cdots, a_k)$ as the minimum data rate vector.

1.3 Problem Formulation

From the network administrator's point of view, we are interested in maximizing the overall network revenue by dynamic pricing and satisfy the quality of service of different users. The formal problem is defined as follows:

$$\max \quad \Big\{\lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\sum_{k\in\kappa}E[q_k(t)R_k(t)]\Big\}, \tag{11}$$

$$\text{s.t.} \quad \left.\begin{array}{l} \displaystyle\sum_{k\in\kappa}P_{r_m,d_k}(t) \leqslant P_{r_m}^{\mathrm{tot}}, \quad \forall m \in \mathcal{M} \\ \text{network stability} \end{array}\right\}, \tag{12}$$

where the first constraint indicates that the power consumption of each user should not exceed its power threshold $P_{r_m}^{\mathrm{tot}}$ to consider energy saving for the cooperative network. Note that a queue is called stable is $\lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}E[Q(t)] < \infty$. A network is stable if all individual queues of the network are stable[10]. So the constraint of network stability can also be expressed as:

$$\begin{cases} \lim\limits_{T\to\infty} \dfrac{1}{T}\sum\limits_{t=0}^{T} E[Q_k(t)] < \infty, \quad \forall k \\ \lim\limits_{T\to\infty} \dfrac{1}{T}\sum\limits_{t=0}^{T} E[Z_k(t)] < \infty, \quad \forall k \end{cases}.$$

Equation (11) is easier to solve if all the statistic information, such as user arrival rate and channel state are given. Since the accurate statistic information is difficult to obtain, we turn to Lyapunov optimization method to solve Eq. (11).

2 Online Algorithm Design

2.1 Dynamic Pricing and Congestion Control

The dynamic pricing that the BS sets for each flow is obtained by solving the following optimization problem,

$$\left.\begin{aligned} &\max_{q_k(t)} \ \{R_k(t)(V_{q_k}(t) - Q_k(t) + Z_k(t))\} \\ &\text{s.t. } R_k(t) = \arg \max_{y_k\in[0,A_k(t)]} (U_k(y_k(t)) - \\ &\qquad q_k(t)y_k(t)) \\ &\quad U_k(y_k(t)) = \lg(1 + y_k(t)) \end{aligned}\right\}. \tag{13}$$

By some simple manipulation, the instantaneous pricing is

$$q_k(t) = \sqrt{\frac{Q_k(t) - Z_k(t)}{V}}, \tag{14}$$

where V is a parameter used to balance the tradeoff between system revenue and average queue length, which will be discussed in the next section.

Note that the above optimal solution structure of the data rate price Eq. (13) reflects the intrinsic mechanism of our proposed pricing-based congestion control. The intuitive explanation of Eq. (13) is that the administrator charges price $q_k(t)$ in order to maximize its revenue at the cost of buffer usage $R_k(t)Q_k(t)$. When the queue $Q_k(t)$ at the network layer has accumulated much backlogs, it raises the data rate price to discourage users to submit aggressive data rate requests. On the other hand, the virtual queues monitor the achievement of minimum data rate requirements. Equation (14) illustrates that the queue dependent pricing can execute the congestion control as well as maximizes the system revenue.

2.2 Relay Power Allocation

As to the relay power allocation, it is to find the solution to the following sub-problem,

$$\begin{aligned} &\max_{\{P_{r_m,d_k}(t)\}} \sum_{k\in\kappa} Q_k(t)C_k(t) \\ &\text{s.t. } \sum_{k\in\kappa} P_{r_m,d_k}(t) \leqslant P_{r_m}^{\text{tot}}, \quad \forall m \in \mathcal{M}. \end{aligned} \tag{15}$$

It can be proved that $C_k(t)$ is concave with respect to the relay power $P_{r_m,d_k}(t), \forall m \in R(k)$. In the following we will design the distributed relay power allocation algorithm by dual decomposition method. The Lagrange function of inequation (15) is

$$\begin{aligned} L(P_r,\lambda) = &\sum_{k\in\kappa} Q_k(t)C_k(t) + \\ &\sum_{m\in\mathcal{M}} \lambda_{r_m}\Big(P_{r_m}^{\text{tot}} - \sum_{k\in\kappa} P_{r_m,d_k}\Big), \end{aligned} \tag{16}$$

where P_{r_m} is the relay m's transmission power, λ_{r_m} is the Lagrange multiplier for the total transmission power constraint for each relay m, $P_r = \{P_{r_m,d_k} | \forall m, \forall k\}$, $\lambda = \{\lambda_{r_1}, \lambda_{r_2}, \cdots, \lambda_{r_m}\}$. The dual problem of Eq. (16) is

$$\min_{\lambda\succcurlyeq 0} \mathcal{D}(\lambda), \tag{17}$$

where "$\succcurlyeq$" is in element-wise manner, $\mathcal{D}(\lambda) = \max\limits_{P_r\succcurlyeq 0} L(P_r,\lambda)$. Due to the concavity of inequation (15) there is no duality gap between inequation (15) and expression (17). After substituting the first-phase SNR Eq. (1) and the second-phase SNR Eq. (6) into inequation (15), we obtain the optimal relay power allocation algorithm by setting the derivative of $L(P_r,\lambda)$ with respect to P_{r_m,d_k} equal to zero,

$$P_{r_m,d_k}^* = \left(\frac{G_{m,k} - P_{s_k}H_{s_k,r_m} - \sigma^2}{H_{r_m,d_k}}\right)^+, \tag{18}$$

where

$$\begin{aligned} G_{m,k} = &\frac{\lambda_{r_m}P_{s_k}H_{s_k,r_m}(P_{s_k}H_{s_k,r_m} + \sigma^2)}{2u_{m,k}} + \\ &\Big\{[\lambda_{r_m}P_{s_k}H_{s_k,r_m}(P_{s_k}H_{s_k,r_m} + \sigma^2)]^2 + 4u_{m,k}v_{m,k}\Big\}^{\frac{1}{2}} \Big/ \\ &(2u_{m,k}), \end{aligned} \tag{19}$$

$$u_{m,k} \triangleq \lambda_{r_m}(b_{m,k}\sigma^2 + P_{s_k}H_{s_k,r_m}), \tag{20}$$

$$\begin{aligned} v_{m,k} \triangleq &\frac{Q_k(t)W}{2\ln 2} P_{s_k}H_{s_k,r_m}P_{s_k}H_{r_m,d_k} \times \\ &(P_{s_k}H_{s_k,r_m} + \sigma^2), \end{aligned} \tag{21}$$

$$\begin{aligned} b_{m,k} \triangleq &1 + \frac{P_{s_k}H_{s_k,d_k}}{\sigma^2} + \\ &\sum_{n\in R(k), n\neq m} \frac{P_{s_k}P_{r_n,d_k}H_{s_k,r_n}H_{r_n,d_k}}{\sigma^2(P_{s_k}H_{s_k,r_n} + P_{r_n,d_k}H_{r_n,d_k} + \sigma^2)}. \end{aligned} \tag{22}$$

The dual problem expression (17) can be solved by the gradient projection method

$$\begin{aligned} &\lambda_{r_m}(i+1) = \\ &\quad \Big\{\lambda_{r_m}(i) + \varsigma\Big[\sum_{k\in\kappa} P_{r_m,d_k}^*(t,i) - P_{r_m}^{\text{tot}}\Big]\Big\}^+, \end{aligned} \tag{23}$$

where $\varsigma > 0$ is a small enough step size to guarantee the convergence of Eq. (23) and i denotes the inner loop iteration index given current time slot t.

From the power allocation policy in Eq. (18), we can find that the relay m will allocate more relay power to the flow of user k, if the buffer of user k stores more packets waiting for transmission than other buffers.

3 Performance Analysis

In this section, we provide the main results on the performance and stability of the proposed algorithms. We have the following theorem.

Theorem 1 Let V^* be the optimal value of the objective function in expression (11). For the proposed joint dynamic pricing and relay power control algorithms, we have the following results,

$$\lim_{T\to\infty}\Big\{\sup\frac{1}{T}\sum_{t=0}^{T-1}E\big[\sum_{k\in\kappa}Q_k(t)\big]+\sum_{k\in\kappa}Z_k(t)\Big\}\leqslant\frac{\varPsi+V\varPhi_{\max}}{\varepsilon},\tag{24}$$

$$\lim_{T\to\infty}\Big\{\inf\frac{1}{T}\sum_{t=0}^{T-1}E\big[\sum_{k\in\kappa}q_k(t)R_k(t)\big]\Big\}\geqslant V^*-\frac{\varPsi}{V},\tag{25}$$

where ε is defined in the following lemma, $\varPsi$ is defined in the proof of Lemma 1 and $\varPhi_{\max}$ is the maximum instantaneous system revenue satisfying: $\sum_{k\in\kappa}q_k(t)R_k(t)\leqslant\varPhi_{\max}$.

From inequations (24) and (25), we can find that a larger V contributes to better net income to the optimal, while increases the queue backlog as well. Hence, our algorithm captures the tradeoff between net income maximization and network stability. We prove the theorem by comparing the proposed algorithms expressions (13)—(23) with some randomized stationary policy.

Lemma 1[10] Assuming all the channel states $I(t)$ are independent and identically distributed, there exists a randomized stationary policy (STAT) that makes dynamic pricing and relay power allocation every time slot only based on the current channel state $I(t)$ and satisfies the following results for $\varepsilon=\min\{\varepsilon_1,\varepsilon_2\}>0$:

$$\left.\begin{array}{l}E[C_k^{\mathrm{STAT}}(t)-R_k^{\mathrm{STAT}}(t)]\geqslant\varepsilon_1,\quad\forall k\\ E[R_k^{\mathrm{STAT}}(t)-a_k]\geqslant\varepsilon_2,\quad\forall m\\ \sum_{k\in\kappa}E[q_k^{\mathrm{STAT}}(t)R_k^{\mathrm{STAT}}(t)]=V^*\end{array}\right\}.\tag{26}$$

Proof Let $\boldsymbol{\gamma}(t)=[Q_k(t)\quad Z_k(t)]$ be the collection of all queue in time slot t. Then we define the following Lyapunov function as:

$$L(\boldsymbol{\gamma}(t))=\frac{1}{2}\Big[\sum_{k\in\kappa}Q_k^2(t)+\sum_{k\in\kappa}Z_k^2(t)\Big].$$

In addition, we define the conditional Lyapunov drift as

$$\Delta L(\boldsymbol{\gamma}(t))=E[L[\boldsymbol{\gamma}(t+1)-L(\boldsymbol{\gamma}(t))]|\boldsymbol{\gamma}(t)].$$

Based on the queueing dynamics Eq. (8), we can get

$$\begin{aligned}&\frac{1}{2}\sum_{k\in\kappa}[Q_k^2(t+1)-Q_k^2(t)]\leqslant\\&\quad\frac{1}{2}\sum_{k\in\kappa}\{C_k^2(t)+R_k^2(t)-2Q_k(t)[C_k(t)-R_k(t)]\}\leqslant\\&\quad\frac{K}{2}(C_{\max}^2+A_{\max}^2)-\sum_{k\in\kappa}Q_k(t)[C_k(t)-R_k(t)],\end{aligned}\tag{27}$$

where $A_{\max}=\max_{k\in\kappa}\{A_k^{\max}\}$, $C_{\max}=\max_{k\in\kappa,t}C_k(t)$. Since each relay has the finite power constraint $P_{r_m}^{\mathrm{tot}}$ and each link has finite channel gain, we can always find the maximum capacity $C_{\max}$ among all users' service rate. Using the inequality (27) and queuing dynamics Eq. (10) similarly, the conditional Lyapunov drift under any control policy can be computed as follows:

$$\begin{aligned}&\Delta L(\boldsymbol{\gamma}(t))\leqslant\\&\quad\varPsi-\sum_{k\in\kappa}Q_k(t)E[(C_k(t)-R_k(t))|\boldsymbol{\gamma}(t)]-\\&\quad\sum_{k\in\kappa}Z_k(t)E[(R_k(t)-a_k)|\boldsymbol{\gamma}(t)],\end{aligned}\tag{28}$$

where

$$\varPsi=\frac{K}{2}(C_{\max}^2+3A_{\max}^2).\tag{29}$$

For a given parameter V, we subtract the objective function $VE[\sum_{k\in\kappa}q_k(t)R_k(t)|\boldsymbol{\gamma}(t)]$ from both sides of inequation (28),

$$\begin{aligned}&\Delta L(\boldsymbol{\gamma}(t))-VE[\sum_{k\in\kappa}q_k(t)R_k(t)|\boldsymbol{\gamma}(t)]\leqslant\\&\quad\varPsi-\sum_{k\in\kappa}E[-Q_k(t)R_k(t)+Z_k(t)R_k(t)+\\&\quad Vq_k(t)R_k(t)|\boldsymbol{\gamma}(t)]-\sum_{k\in\kappa}E[Q_k(t)C_k(t)|\boldsymbol{\gamma}(t)]+\\&\quad\sum_{k\in\kappa}Z_k(t)a_k.\end{aligned}\tag{30}$$

Comparing inequation (30) with the proposed dynamic pricing algorithms Eq. (13) and relay power allocation schemes inequation (15), we can find that the proposed algorithms Eqs. (13) and (14) and inequation (15) intend to minimize the right hand side of inequation (30) over all possible control schemes every time slot, including the randomized stationary policy STAT expression (26). By substituting expression (26) into inequation (30), we have,

$$\Delta L(\boldsymbol{\gamma}(t)) - VE[\sum_{k\in\kappa} q_k(t)R_k(t)|\boldsymbol{\gamma}(t)] \leqslant \Psi - \varepsilon\Big(\sum_{k\in\kappa} Q_k(t) + \sum_{k\in\kappa} Z_k(t) - VV^*\Big). \quad (31)$$

Summing inequation (31) over time slots $t \in \{0, 1, \cdots, T-1\}$ and dividing by T yields:

$$\frac{E[L(\boldsymbol{\gamma}(T)) - L(\boldsymbol{\gamma}(0))]}{T} - \frac{V}{T}\sum_{t=0}^{T-1} E\Big[\sum_{k\in\kappa} q_k(t)R_k(t)|\gamma(t)\Big] \leqslant \Psi - \frac{\varepsilon}{T}\sum_{t=0}^{T-1} E\Big[\sum_{k\in\kappa} Q_k(t) + \sum_{k\in\kappa} Z_k(t)\Big] - VV^*. \quad (32)$$

Due to the non-negative of Lyapunov function and the objective function in Eq. (13) as well as

$$\sum_{k\in\kappa} q_k(t)R_k(t) \leqslant \Phi_{\max}, \quad (33)$$

$$\frac{1}{T}\sum_{t=0}^{T-1} E\Big[\sum_{k\in\kappa} Q_k(t) + \sum_{k\in\kappa} Z_k(t)\Big] \leqslant \frac{\Psi + V\Phi_{\max}}{\varepsilon} + \frac{E[L(\boldsymbol{\gamma}(0))]}{T\varepsilon}. \quad (34)$$

After dividing both sides of inequation (32) by ε, taking the lim sup as $T \to \infty$ inequation (24) can be obtained. The system revenue is also upper bounded by rearranging (32),

$$\frac{1}{T}\sum_{t=0}^{T-1} E\Big[\sum_{k\in\kappa} q_k(t)R_k(t)\Big] \geqslant V^* - \frac{1}{V}\Big(\Psi + \frac{E[L(\boldsymbol{\gamma}(0))]}{T}\Big). \quad (35)$$

Taking the lim inf as $T \to \infty$ on both sides of inequation (35) yields inequation (25).

4 Simulation Results

In this section, we present simulation results to evaluate the performance of our algorithm. We initialize the cellular network with $K = 20$ users and $M = 6$ relays. These end users and relays are deployed in a 200 m × 200 m region shown in Fig. 1, where the six relays are fixed at the positions of (20, 100), (50, 100), (80, 100), (110 100), (140, 100) and (170, 100) m, respectively. These sources and destinations are generated randomly in the area and their positions are shown in Fig. 1. The channel gain of any transmission pair consists of a small-scale Rayleigh fading component and a large-scale pass loss component with pass loss factor of 4. The noise variance σ^2 is assumed to be 10^{-10}. Each relay has the same instantaneous transmission power constraints $P_{r_m}^{\text{tot}} = 10$ W. The source uses constant transmission power 5 W for uplink transmission. Similarly, all the twenty users are supposed to have equal minimum transmission rate requirements. We divide the twenty users into four different classes randomly and the uplink average arrival rate of the four classes users are [0.2, 0.4, 0.6, 0.8] packets/slot, respectively.

Figure 2 illustrates the processing tendency of users' backlogs $Z_k(t)$ during 1 500 time slots. For brevity, we depict the queue backlogs of four users from four different classes, indicated as C_1, C_2, C_3 and C_4, with average requested rate 0.2, 0.4, 0.6 and 0.8 during 1 500 time slots respectively. As is depicted in Fig. 2, the backlog queue is bounded and reaches a converged value after a long time. Thus the system stability is verified, and admitted data rate is smaller than service rate.

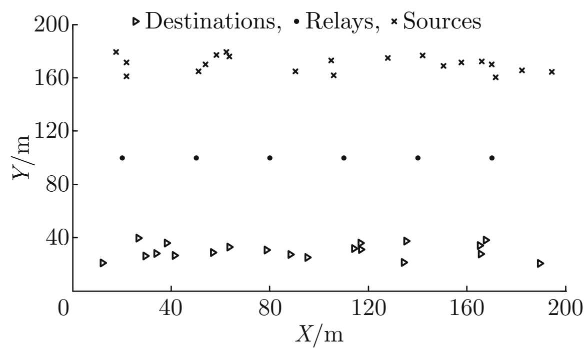

Fig. 1 Network model

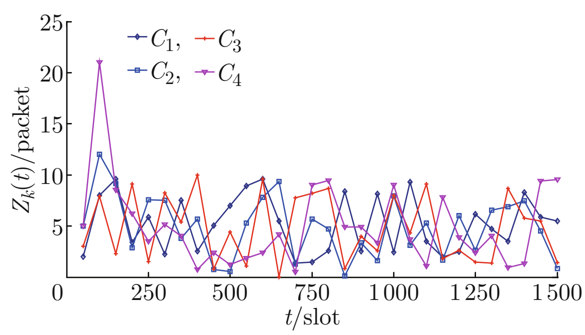

Fig. 2 Users' queue length dynamics

Figure 3 illustrates the queue length dynamics of user 2 with respect to different parameter V. The other nineteen users have the similar queuing tendency. As depicted in Fig. 3, a larger V results in a larger average queue length, which coincides with the algorithmic performance in Theorem 1.

We further illustrate the system performance in terms of network revenue in Fig. 4. Figure 4 demonstrates that the system revenue increases with the parameter V, which is consistent with inequation (25).

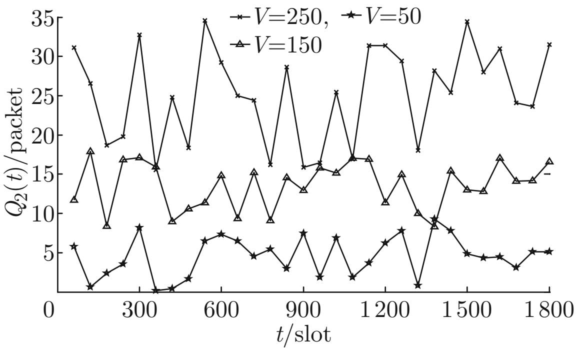

Fig. 3 Users' actual queue length with different V

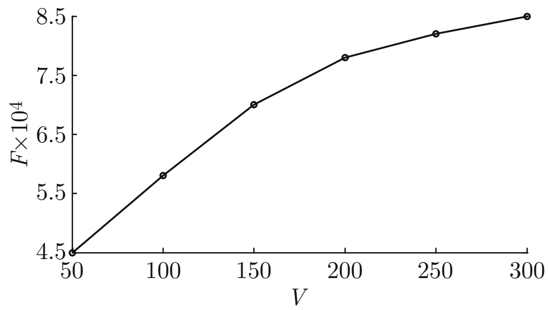

Fig. 4 Total system revenue (F) versus parameter V

Then by adjusting parameter V, we can achieve the tradeoff between optimality and queue length. According to little's law, the larger system revenue is obtained at the cost of larger queuing delay.

5 Conclusion

In this paper, we investigate the dynamic pricing and congestion control for uplink transmission in a relay-assisted cellular network to maximize the network's revenue from the perspective of network administrator. We propose a dynamic pricing algorithm jointly with relay power allocation to tackle the problem of coordinating users' random rate requirement, network resource allocation and network revenue maximization problem. Theoretical analysis and simulation results show that our proposed algorithm achieves a tradeoff between network stability and performance optimality.

References

[1] Lou S J, Yang L X. Joint relay selection and power allocation for two-way relay channels with asymmetric traffic requirements [J]. *KSII Transactions on Internet and Information Systems*, 2013, **7**(8): 1955-1971.

[2] Le L, Hossain E. Cross-layer optimization frameworks for multi-hop wireless networks using cooperative diversity [J]. *IEEE Transactions on Wireless Communications*, 2008, **7**(7): 2592-2602.

[3] Lou S J, Yang L X. Performance analysis of joint relay selection and power allocation for two-way relay channels [C]//*International Conference on Computer, Networks and Communication Engineering 2013*. Beijing, China: Atlantis Press, 2013: 455-460.

[4] Xu, H, Li B C. Resource allocation with flexible channel cooperation in cognitive radio networks [J]. *IEEE Transactions on Mobile Computing*, 2013, **12**(5): 957-970.

[5] Cao Q, Jing Y D, Zhao H V. Power allocation in multi-user wireless relay networks through bargaining [J]. *IEEE Transactions on Wireless Communications*, 2013, **12**(6): 2870-2882.

[6] Moghadari M, Hossain E, Le L B. Delay-optimal distributed scheduling in multi-user multi-relay cellular wireless networks [J]. *IEEE Transactions on Communications*, 2013, **61**(4): 1349-1360.

[7] Urgaonkar R, Neely M J. Delay-limited cooperative communication with reliability constraints in wireless networks [C]//*Proceedings of IEEE International Conference on Computer Communications 2009*. Rio de Janeiro, Brazil: IEEE, 2009: 2561-2565.

[8] Pham N T, Huynh T, Hwang W J. Throughput-optimal scheduling for cooperative relaying in wireless access networks [J]. *EURASIP Journal on Wireless Communications and Networking*, 2012, **2012**(1): 70.

[9] Hadef M, Apostolaras A, Mourad A, et al. Energy efficiency performance evaluation of back-pressure driven cooperative relay selection for WiMAX systems [C]//*Proceedings of the 6th International ICST Conference on Simulation Tools and Techniques*. Cannes, France ICST, 2013: 258-267.

[10] Neely M J. Stochastic network optimization with application to communication and queueing systems [J]. *Synthesis Lectures on Communication Networks*, 2010, **3**(1): 1-211.

[11] Hande P, Chiang M, Calderbank A R, et al. Pricing under constraints in access networks: Revenue maximization and congestion management [C]//*Proceedings of IEEE on INFOCOM 2010*. San Diego, CA, United States: IEEE, 2010: 1-9.

[12] Li S Q, Huang J W. Price differentiation for communication networks [EB/OL]. (2013-05-05) [2014-05-01] http://arxiv.org/abs/1011.1065.

[13] Li S Q, Huang J W, Li S Y R. Dynamic profit maximization of cognitive mobile virtual network operator [J]. *IEEE Transactions on Mobile Computing*, 2014, **13**(3): 526-540.

[14] Huang L B, Neely M J. The optimality of two prices: Maximizing revenue in a stochastic communication system [J]. *IEEE/ACM Transactions on Networking*, 2010, **18**(2): 406-419.

[15] Song Y, Zhang C, Fang Y, et al. Revenue maximization in time-varying multi-hop wireless networks: Dynamic pricing approach [J]. *IEEE Journal on Selected Areas in Communications*, 2012, **30**(7): 1237-1245.