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***Abstract*—In this work, we address the problem of decentralized power allocation for satisfying individual QoS constraints in video streaming in a Small Cells Network.They QoS metric we use here is the probability that the queue length at each transmitter exceeds some threshold: we want this probability to be fixed at a desired value. We focus on a model with interfering transmitter-receiver pairs. Using heavy traffic asymptotic modelling we propose a power control algorithm for the case where each base station has access to local SINR feedback, information about the queue length of its user and delayed information of the queues in the other base stations. Simulation results suggest that the proposed algorithm is quite robust in the case of delayed information sharing.**

I. Introduction

A. Video Provisioning in Small Cell Networks

Current wireless networks experience an increasing demand on offered services to end users as well as the necessity to ensure high quality of service and data rates of the provided applications. A promising way to deal with these demands is the concept of Small Cell Networks (SCN), which are dense cellular networks with low power base stations and full frequency reuse one [1], able to provide higher spectral efficiencies.

One of the key issues arising in these networks is that the intercell interference becomes severe. Also, video applications are becoming more and more important in mobile networks for both service providers and users. These applications have hard requirements in terms of Quality of Service, as they are delay-sensitive and also require transfer of big amounts of data to ensure high quality at the end users. Currently, the infrastructure of wireless networks does not provide enough support for the Quality of Service required for streaming high quality video. Therefore, there is a need for dynamic resource allocation algorithms (like power control, bandwidth allocation, scheduling, rate adaptation, coding...) to be designed, taking into account the requested video content, traffic requirements and QoS constraints. Additionally, an issue in Small Cell Networks is the limited and diverse backhaul. This limits the control information that can be exchanged between the Base Stations, making full coordination very difficult. Typically, each base station will have only local information (e.g. about the channels and queues of the users that are attached to it) and delayed versions of the information about the other base stations (due to the limited backhaul for signalling).

B. Assumptions and Problem Statement

In this work we focus on the power control problem at the Base Stations of a Small Cell Network taking into account the incoming traffic characteristics of the requested video streams so that the Quality of Service criteria are met. Traditionally power control is used to satisfy some SINR constraints and/or to maximize the systems totel throughput, without taking the incoming traffic into account [2]. In this work, we consider a system of K interfering transmitter-receiver pairs, as depicted in Figure 1. The traffic arriving at each user is assumed to be independent with finite mean λ_k and variance $\sigma^2_{a,k}$ and the channels gains from base station i to receiver j , g_{ij} are assumed to evolve as finite state ergodic Markov chains [3], and independent with each other and the arrival processes. This setting can correspond to a Small Cell Network of K cells with frequency reuse 1, using the same subcarriers to serve the users, where each user is attached to one cell. Also, we assume that the channels change slower than the arrivals, meaning that within a channel coherence time there are many bits arriving at each base station. The transmission rates are given as Shannon rates treating interference as noise. For convenience (and without any loss of generality) we index the base stations and the users so that user k is served by base station k. The Quality of Service aspect on which we focus is the data loss due to buffer overflows or, most importantly for the delay constrained nature of video applications, the probability that the delay in the queue of each transmitter k, exceeds some threshold, which must be set to some desired value δ_k. Via, for example, Littles law [**?**], we can choose an appropriate queue length threshold, q_k^{thr} , so that our aforementioned goals correspond to setting the probability that the queue length $g_k(t)$ at each transmitter k exceeds a specified threshold at the desired value, namely

$$Pr\left\{q_k(t) > q_k^{thr}\right\} = \delta_k \qquad (1)$$

which means setting a buffer (equivalently, delay) outage probability in some values that can be tolerated by the application.

Note that these overflow constraints have to be met for any transmitter individually. In a recent previous work [4], we considered a centralized approach with full knowledge of CSI and the queue lengths at each transmitter. The main idea of the proposed algorithm is to allocate the biggest fraction of power according to the channel states and mean arrival rate of the requested stream and then add a small amount of reserve power according to the queue lengths to adapt to the instantaneous traffic pattern.

In this paper, we move to a more decentralized approach where we assume that each base station has access ti the following information:

- Local SINR feedback (i.e. feedback from the user attached to it only) and its own queue length
- Delayed information of the queue lengths at the other base stations
- The statistics of the traffic at the other base stations, model parameters

After a brief discussion of the heavy traffic model in Section II, we propose in Section III a power control algorithm under the above conditions. We give numerical results for a simple setting in Section IV. Finally, Section V concludes the paper.

II. Heavy traffic System Model and Power Control Policy

The approach followed is based on the heavy traffic asymptotic modeling. In this method, the network is examined for the case when the offered traffic is almost equal to the mean service rate. Then, the system model becomes more tractable to study analytically in order to obtain control strategies. Our model is an extension of [5] and [6], where this method was used for power control in a point-to-point link and a single cell multiuser system respectively, to a full interference scenario. Basically, the power is allocated in two steps: one part is according to the channels so that the average rate is equal to the average incoming traffic rate (equilibrium allocation) and then a small reserve amount (reserve allocation) is added for the system to adapt to the instantaneous traffic dynamics and satisfy the QoS requirements. The motivation for this reserve power allocation is that when the average rate equals the average input rate the delay becomes unbounded [5], [7].

As discussed in [4], a way to satisfy (1) in a centralized setting is to allocate the power at transmitter k in two steps: (i) Allocate an equilibrium power such that the mean service rates match the mean arrival rates (ii)add some small reserve power u_k depending only on the queue lengths at the time of the allocation. Small reserve power implies that the average service rates are very close to the average incoming rates. This case corresponds to the so-called Heavy traffic asymptotic regime of the network [8] and the evolution of the vector of the queue lengths over time can be approximated analytically as [4]

$$d\mathbf{x}(t) = \mathbf{B}\mathbf{x}(t)dt + \mathbf{\Sigma}d\mathbf{w}(t) + d\mathbf{z}(t) \qquad (2)$$

In the above, $\mathbf{x}(t)$ represents the queue lengths in the approximate model, $\mathbf{B}$ is a matrix with elements that correspond to the effect that power allocation in a transmitter has on the transmission rate of the others. The first term corresponds to the change of the queue lengths due to the reserve power allocation. The second term is a random term ($\mathbf{w}$ is a vector of Wiener processes and its differential can be viewed as a white noise). It models the change of the queue lengths due to the (random) arrivals and equilibrium power allocation: as the equilibrium power depends only on the channel states and these change at random, the corresponding rate is also random. The third term is required to keep the queue lengths positive and represents wasted service when power is allocated at a transmitter whose queue is empty.

Based on this model, the proposed solution in [4] is, at every time slot l, to have the equilibrium power allocation p(l) such that the corresponding SINR is the same for each realization of the channels and the corresponding rates are equal to the mean arrival rates at each base station. Then, there is added a vector of reserve powers of the form

$$\mathbf{u}(l) = \mathbf{B}^{-1}\mathbf{C}\mathbf{q}(l) \qquad (3)$$

In the above, $\mathbf{q}(l)$ is the vector of the queue lengths in the system at the beginning of this timeslot and $\mathbf{C}$ a matrix properly derived from the asymptotic model as $\mathbf{C} = \text{diag}\left\{\frac{1}{2}\left(\frac{\sigma_{a,k}}{q_k^{thr}} erfc^{-1}(\delta_k)\right)^2\right\}$.

III. Control Policies under Imperfect State Information

In practical systems, it is desirable that the power control is done in a way that is as decentralized as possible. More specifically, it is unrealistic to suppose that each transmitter has knowledge of every channel realization in the network. However, it is reasonable that the queue state information is exchanged with delays (e.g. due to limited backhaul for the coordination among the transmitters). We address these issues separately:

A. Local SINR Feedback

First we will examine the case where each receiver can send SINR feedback to its corresponding transmitter but other than that no information on the channels is available. Observing that the equilibrium power allocation is such that the corresponding rate is constant, that is a scenario where users request a fixed target SINR, we can use the algorithm proposed in [9] to find the equilibrium power allocation without the need for global knowledge of the channel states. More specifically, for a system adjusting the power in discrete time, in the beginning of each time slot of duration T_s, we can dedicate a training time τ where the transmitters find the equilibrium power as in Fig. 2. In order to do that, each transmitter k requires only the SINR feedback from its corresponding receiver and runs the following iterative process

$$p_k(i+1) = \frac{\bar{\gamma}_k}{\gamma_k(i)} p_k(i) \tag{4}$$

where i denotes here the iteration of the algorithm, $\bar{\gamma}_k$ the target SINR of user k and $\gamma_k(i)$ the SINR at this user after the power update of iteration i. It is shown in [9], that this algorithm indeed converges to the equilibrium values corresponding to these channels and moreover this convergence is very fast. Data transmission is performed for the rest duration $T_s - \tau$ of the timeslot, with the reserve power allocated as discussed in the next Subsection.

Since the parameters of the asymptotic model in (2) and the reserve power control policy (3) actually depend on the bandwidth, a way to incorporate the effect of the training phase in the model is to assume that the available bandwidth for transmission is actually $\frac{T_s - \tau}{T_s} W$, where W is the bandwidth physically available, and change the rate expressions accordingly.

B. Delayed Queue State Information

A major issue for the practical implementation of our control policy is the requirement that each transmitter is aware of all the queue lengths instantaneously. A more realistic assumption would be that each transmitter knows its own instantaneous queue state and has access to delayed information about the queues of the others. For example, this can correspond to a Small Cell Network setting where the base stations exchange information using a backhaul of limited capacity. We will assume though that each transmitter still knows the statistics of the arrivals to the other transmitters, the parameters of the asymptotic model and the matrix $\mathbf{C}$ in the reserve control policy (3).

We propose a simple heuristic approach where each transmitter calculates the transmission power with the queue length vector being replaced with the vector of the most recent information about the queue states this transmitter has. That means that transmitter k calculates (3) using the delayed queue state information about the other transmitters in the queue length vector. Then, it picks the k-th element of the resulting vector to add to the equilibrium power as the reserve power.When there are no information yet about the queue at a transmitter, the standard deviation of the incoming traffic at this transmitter is used as an estimation of the queue length. Note that the algorithm supposes that the parameters of the asymptotic model and the statistics of the traffic are available (in order to calculate the reserve control policy).

IV. Numerical Results

In order to illustrate the results of the power control method proposed in this paper, let us consider a simple scenario with 3 interfering transmitter - receiver pairs, using a the same spectrum with bandwidth $5MHz$. For simplicity, we considered that each channel gain has only two possible values. Also, the arrivals at each transmitter were set as Poisson processes with mean rates 1, 1.5 and 2 Mbps. The overflow thresholds were set to $500, 750, 1000$ bits at each transmitter respectively and the overflow probability to 0.01 for all transmitters. The coherence time of the channels will be set to $20msec$ and the timeslot duration to $2msec$, thus the channel stays the same for 10 consecutive power configurations. The noise variance was set to 0.01 at each receiver.

The channel states were set such that each channel gain has only two possible values. All the 'equilibrium' powers are in the order of magnitude of mW. The expected values of the equilibrium powers over the ergodic distribution of the channel gains matrix was found to be W, W, W for transmitters 1, 2 and 3 respectively. Also, for our proposed algorithm simulations showed that the reserve power allocated is in the order of magnitude of $10^{-5}W$, thus the assumption of the reserve power being much smaller than the equilibrium power is confirmed by simulations. Besides , the average reserve powers used where found (by simulations) to be around $0.7 \times 10^{-5}W, 0.7 \times 10^{-5}W, 0, 8 \times 10^{-5}W$.

We run 200 simulations each having the duration of 100000 time slots and study effect of delayed queue state information in our algorithm. For simplicity, all the delays in information sharing between the transmitters delays are set to be the same.

As illustrated in Fig. 2, at each time slot we first run the algorithm (4) for a few iterations to tune the equilibrium power; an example is shown in Fig. 3, where we can see that the iterations needed for convergence are very few, thus a small training time is required. Then, we add the reserve power according to the delayed queue length information as discussed in Section III.B and use the remaining timeslot for data ransmission.

The performance in terms of overflow ratios are given in Fig. 4. Due to space limitations, results concerning the overflow ratios are depicted for transmitter 1 only. The results for the other transmitters are similar though. As we can see in this figure, as the delay in information sharing increases the overflow ratios tend to be higher. However, especially for small delays, the differences are still relatively small. Thus we can argue that if we know the incoming traffic statistics at each base station, our proposed scheme seem to be quite robust in cases of delayed information sharing.

Finally, Fig. 5 shows an example of the evolution of the power allocation from our proposed policy versus the equilibrium power allocation. We can see that the reserve power is indeed very small compared to the equilibrium power.

V. Conclusions

In this work we extended our previous work based on heavy traffic asymptotic models and proposed a power control algorithm requiring just local SINR feedback and knowledge of the statistics of the channels and traffic in all transmitters of the network. Simulation results imply that this algorithm is robust and can have good performance the case where each transmitter has imperfect state information.

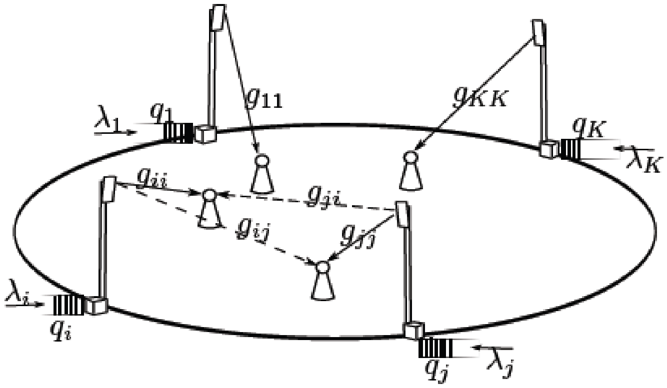

Fig. 1: Illustration of the system model.

Fig. 2: Illustration of the phases of a time slot when only local SINR feedback is available.

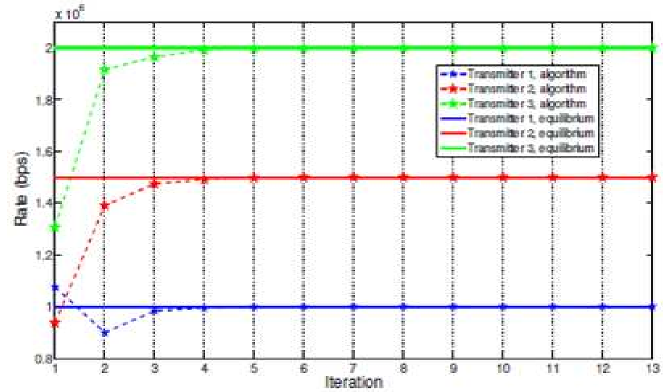

Fig. 3: Example of iterations needed in the training phase to converge to the equilibrium rates.

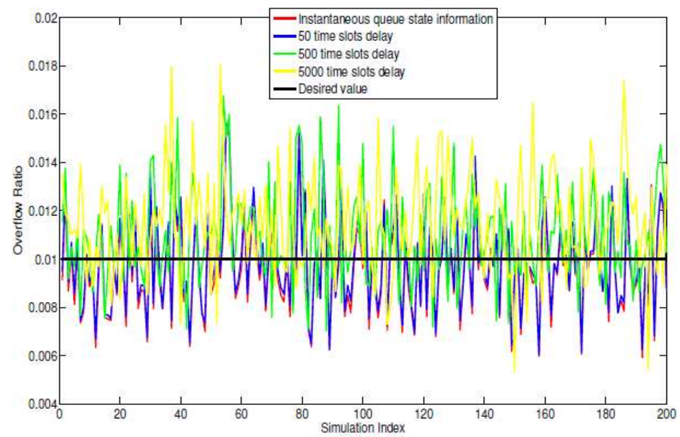

Fig. 4: Overflow ratios for the proposed algorithm implemented with delayed information for Link 1.

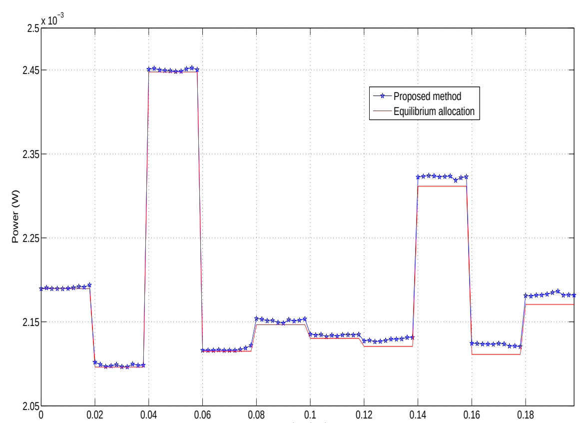

Fig. 5: Example of the evolution of the equilibrium and allocated power for Link 1 using our method for the first 100 timeslots of a simulation.

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